Antenna-Diversity-Assisted Genetic-Algorithm-Based Multiuser Detection Schemes for Synchronous CDMA Systems

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***Abstract*—A spatial diversity reception assisted multiuser code-division multiple-access detector based on genetic algorithms (GAs) is proposed. Two different GA-based individual-selection strategies are considered. In our first approach, the so-called individuals of the GA are selected for further exploitation, based purely on the sum of their corresponding figures of merit evaluated for the individual antennas. According to our second strategy, the GA's individuals are selected based on the concept of the so-called Pareto optimality, which uses the information from the individual antennas independently. Computer simulations showed that the GAs employing the latter strategy achieve a lower bit-error rate as compared to the former strategy. For a 15-user GA-assisted system employing a spreading factor of 31, a complexity reduction factor of 81 was achieved at a performance identical to that of the optimum multiuser detector using full search.**

***Index Terms*—Antenna diversity, genetic algorithms, multiuser detection, synchronous code-division multiple access (CDMA).**

I. Introduction

IT IS WELL KNOWN that the optimum full-search-based multiuser detector proposed by Verdú [1] has a computational complexity that is exponentially increasing with the number of users. Hence, it is impractical to implement. This limitation led to numerous so-called suboptimal multiuser detection proposals, highlighted by Verdú in his monograph [2] and in the references therein. The suboptimum detectors sacrifice performance for the sake of a reduced complexity.

Multiuser detection based on genetic algorithms (GAs) [3], [4] has been proposed by Juntti *et al.* [5] and Wang *et al.* [6], where the analysis was based on the additive white Gaussian noise (AWGN) channel without using diversity techniques. The proposal by Ergün *et al.* [7] utilized the GA as the first stage of a multistage multiuser detector, in order to provide good initial guesses for the subsequent stages. Its employment in Rayleigh fading channels was considered by Yen *et al.* [8], [9] in the absence of diversity techniques.

In this letter, we present a novel approach to the problem of multiuser detection in direct sequence code-division multiple access (DS/CDMA) over Rayleigh fading channels assisted by antenna diversity [10] based on a GA innovation. The antennas are assumed to be sufficiently separated such that the received signals at the antennas are faded independently, resulting in an independent log-likelihood function (LLF) [1] for each antenna. This poses a problem to the optimization process due to the fact that while a specific K-bit vector representing the current bit of the K users supported may be deemed optimum on the basis of the LLF of one antenna, the same bit sequence may not necessarily be deemed optimum in terms of the LLF of the other antenna. In order to resolve this dilemma, two different GA-based individual-selection strategies are considered. In our first approach, the individuals of the GA [3], [4] representing the K-bit vector of the K users are selected for further exploitation, based purely on the sum of their corresponding LLFs or figures of merit based on the two antennas. This approach is analogous to invoking the conventional LLF for diversity reception [11]. According to our second strategy, the individuals associated with the GA are selected based on the concept of the so-called Pareto optimality [3], which uses the information from the antennas independently.

This paper is organized as follows. Section II describes our synchronous CDMA system communicating over uncorrelated nonfrequency-selective fading channels using two antennas. Section III describes the GAs used to implement our proposed detector in conjunction with diversity reception. Our simulation results and complexity issues are presented in Section IV, while Section V concludes the letter.

II. System Description

We consider a K-user symbol-synchronous CDMA system, where the receiver, shown in Fig. 1, consists of two antennas separated spatially, such that the signals received are statistically independent. At each antenna, a bank of filters matched to the corresponding set of the users' signature sequences is sampled at the end of each bit interval. Hence, the output $\boldsymbol{z}_i$ of the matched filter bank at the ith diversity antenna is given by the vector

$$\boldsymbol{z}_i = [z_{1,i}, z_{2,i}, \ldots, z_{K,i}]^T = \boldsymbol{R}\boldsymbol{\xi}\boldsymbol{C}_i\boldsymbol{b} + \boldsymbol{n}_i \tag{1}$$

where $\boldsymbol{R} = \int_0^{T_b} \boldsymbol{a}(t)\boldsymbol{a}^T(t)$ is the $K \times K$ cross-correlation matrix of the users' signature sequences, $\boldsymbol{a}(t) = [a_1(t), \ldots, a_K(t)]^T$ is the signature sequence vector for the K users, and $\boldsymbol{\xi} = \mathrm{diag}(\sqrt{\xi_1}, \ldots, \sqrt{\xi_K})$ is the diagonal matrix of the received bit energy for the K users. Furthermore, $\boldsymbol{C}_i = \mathrm{diag}(\alpha_{1,i}e^{j\theta_{1,i}}, \ldots, \alpha_{K,i}e^{j\theta_{K,i}})$ is the channel impulse response (CIR) matrix describing the frequency-nonselective slowly Rayleigh fading channel of each of the K users, $\boldsymbol{b} = [b_1, b_2, \ldots, b_K]^T$ is the current transmitted bit vector of the K users, and $n_i(t)$ is the zero-mean complex additive white Gaussian noise (AWGN) with independent real and imaginary components, each having a double-sided power spectral density of $N_0/2$.

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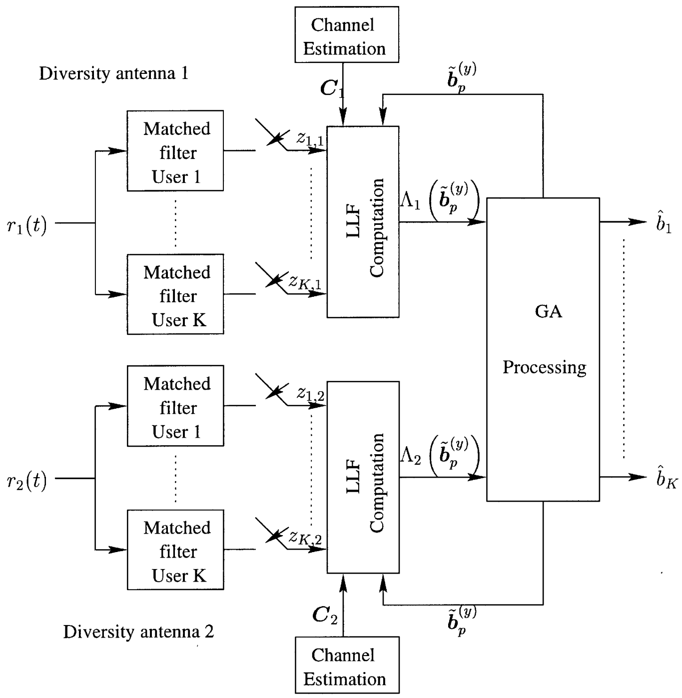

Fig. 1. Block diagram of the receiver model.

Based on the observation vector $\boldsymbol{z}_i$ given in (1), it can be shown that the LLF for the ith antenna is given by [12]

$$\Lambda_i(\boldsymbol{b}) = 2\Re\left\{\boldsymbol{b}^T\boldsymbol{C}_i^*\boldsymbol{\xi}\boldsymbol{z}\right\} - \boldsymbol{b}^T\boldsymbol{C}_i^*\boldsymbol{\xi}\boldsymbol{R}\boldsymbol{\xi}\boldsymbol{C}_i\boldsymbol{b}. \quad (2)$$

The decision rule for the optimum multiuser detector associated with the ith antenna is to choose the bit vector $\hat{\boldsymbol{b}}$, which maximizes the LLF given in (2). Hence, the estimated transmitted bit vector of the K users is given by

$$\hat{\boldsymbol{b}} = \arg\left\{\max_{\boldsymbol{b}}\left[\Lambda_i(\boldsymbol{b})\right]\right\}. \quad (3)$$

Since the channel characteristics for each antenna are statistically independent, we have typically $\Lambda_1(\boldsymbol{b}) \neq \Lambda_2(\boldsymbol{b})$ for the LLFs of the two antennas. In certain scenarios, such as during deep fades, the above inequality implies that

$$\arg\left\{\max_{\boldsymbol{b}}\left[\Lambda_1(\boldsymbol{b})\right]\right\} = \hat{\boldsymbol{b}} \neq \arg\left\{\max_{\boldsymbol{b}}\left[\Lambda_2(\boldsymbol{b})\right]\right\} \quad (4)$$

or vice versa. This creates a so-called multiobjective optimization problem, since the optimization of both LLFs may lead to two possible K-bit solutions. Nevertheless, for optimum detection, the LLFs corresponding to the two diversity antennas are combined according to [11]

$$\begin{aligned}\Lambda(\boldsymbol{b}) &= \sum_{i=1}^{2}\Lambda_i(\boldsymbol{b}) \\ &= 2\Re\left\{\boldsymbol{b}^T\vec{\boldsymbol{C}}^H\vec{\boldsymbol{\xi}}\vec{\boldsymbol{z}}\right\} - \boldsymbol{b}^T\vec{\boldsymbol{C}}^H\vec{\boldsymbol{\xi}}\vec{\boldsymbol{R}}\vec{\boldsymbol{\xi}}\vec{\boldsymbol{C}}\boldsymbol{b} \end{aligned} \quad (5)$$

where $\vec{\boldsymbol{C}} = \mathrm{diag}[(\alpha_{1,1}e^{j\theta_{1,1}}, \alpha_{1,2}e^{j\theta_{1,2}})^T, \ldots, (\alpha_{K,1}e^{j\theta_{K,1}}, \alpha_{K,2}e^{j\theta_{K,2}})^T]$, $\vec{\boldsymbol{z}} = [z_{1,1}, z_{1,2}, \ldots, z_{K,1}, z_{K,2}]^T$, while $\vec{\boldsymbol{\xi}} = \mathrm{diag}[\sqrt{\xi_1}, \sqrt{\xi_1}, \ldots, \sqrt{\xi_K}, \sqrt{\xi_K}]$ and $(\cdot)^H$ denotes a Hermitian matrix. The decision rule is then to find the estimated transmitted bit vector $\hat{\boldsymbol{b}}$ that maximizes $\Lambda(mbib)$ in (5).

In the next section, we will highlight the GA developed for multiuser detection with emphasis on our individual-selection strategy contrived for detecting the users' transmitted bits.

III. GA-Based Multiuser Detection With Diversity Reception

GAs [3], [4] can be invoked in robust global search and optimization procedures that are well suited for solving complex optimization problems. In this letter, we will employ GAs in order to detect the estimated transmitted bit vector $\hat{\boldsymbol{b}}$, where the required objective function is defined by the LLF of (2) for the two antennas.

GAs commence their search for the optimum K-bit solution at the so-called $y = 0$th generation by randomly creating P legitimate K-bit solutions, or so-called *individuals* in GA parlance, where the pth individual is expressed here as $\tilde{\boldsymbol{b}}_p^{(y)} = [\tilde{b}_{p,1}^{(y)}, \tilde{b}_{p,2}^{(y)}, \ldots, \tilde{b}_{p,K}^{(y)}]$. The mechanism behind efficient GA-based optimization is to select potential K-bit candidate individuals from these legitimate individuals and then exploit these selected individuals in the subsequent generation, in order to find the optimal K-bit solution. The selection of the K-bit individuals is vital in determining the quality of optimization by the GA [14]. Hence, two different individual-selection strategies are evaluated here, in order to determine which individuals of a K-bit population are selected for future exploitation.

In our first strategy, each K-bit individual is associated with a fitness value denoted as $\boldsymbol{f}(\tilde{\boldsymbol{b}}_p^{(y)}) = [\Lambda(\tilde{\boldsymbol{b}}_p^{(y)})]$, which is a function of the LLF of (5). Individuals having the T highest fitness values in the population, where $2 \leq T < P$, are then selected and placed in the so-called *mating pool*. Hence, the selection of individuals in the GA-aided optimization employing this strategy is based on the conventional LLF-assisted diversity reception of (5) [11].

Our second individual-selection strategy of the GA-assisted multiuser detection is based on the concept of the so-called Pareto optimality [3]. This strategy favors the so-called nondominated individuals and ignores the so-called dominated individuals. Here, the pth K-bit individual is associated with three fitness values denoted as $\boldsymbol{f}(\tilde{\boldsymbol{b}}_p^{(y)}) = [\Lambda_1(\tilde{\boldsymbol{b}}_p^{(y)}), \Lambda_2(\tilde{\boldsymbol{b}}_p^{(y)}), \Lambda(\tilde{\boldsymbol{b}}_p^{(y)})]$, where the first two fitness values are functions of the LLF of (2), while the third fitness value is a function of the LLF of (5). Then the pth K-bit individual is considered to be dominated by the qth individual iff [13]

$$\begin{aligned}&\forall i \in \{1,2\} : \Lambda_i\left(\tilde{\boldsymbol{b}}_q^{(y)}\right) \geq \Lambda_i\left(\tilde{\boldsymbol{b}}_p^{(y)}\right) \\ &\wedge \exists j \in \{1,2\} : \Lambda_j\left(\tilde{\boldsymbol{b}}_q^{(y)}\right) > \Lambda_j\left(\tilde{\boldsymbol{b}}_p^{(y)}\right). \end{aligned} \quad (6)$$

If an individual is not dominated in the sense of (6) by any other K-bit individuals in the population, then by definition it is considered to be nondominated. *According to our second individual-selection strategy, all the nondominated K-bit individuals are selected and placed in the mating pool.* Hence,

TABLE I
COMPUTATIONAL COMPLEXITY COMPARISON IN TERMS OF THE NUMBER OF MULTIPLICATIONS AND ADDITIONS
INV DENOTES THE COMPUTATION FOR THE INVERSE CORRELATION MATRIX

Correlator	Decorrelator	Proposed	Optimum
$2KN_c$	$2K(K+N_c)+INV$	$[2K(K+N_c)+5K+1]PY$	$[2K(K+N_c)+5K+1]2^K$

the value of $2 \leq T < P$[1] in this case is not fixed, since it depends on the number of nondominated individuals. Observe that the latter strategy uses the LLF-based figure of merit information from both antennas independently in order to decide which individuals are placed in the mating pool. By contrast, our former K-bit individual-selection strategy based its decisions on a single entity by combining the antenna-specific figures of merit according to (5). We shall denote the K-bit individuals in the mating pool as $\breve{\boldsymbol{b}}_q^{(y)}$ for $q = 1, \ldots, T$.

Two K-bit individuals in the mating pool are then selected as *parents* based on their corresponding figure of merit $\Lambda(\breve{\boldsymbol{b}}_q^{(y)})$ in (5) according to a probabilistic function known as *sigma scaling* [4]. Under sigma scaling, the parents-selection probability $p(\breve{\boldsymbol{b}}_q^{(y)})$ of an individual is a function of its own fitness in the sense of (5) as well as that of the mating pool's mean fitness and its associated standard deviation, as formulated below [4]

$$p\left(\breve{\boldsymbol{b}}_q^{(y)}\right) = \begin{cases} 1.0 + \dfrac{\Lambda\left(\breve{\boldsymbol{b}}_q^{(y)}\right) - \bar{\Lambda}}{2\sigma_\Lambda}, & \text{if } \sigma_\Lambda \neq 0 \\ 1.0, & \text{if } \sigma_\Lambda = 0 \end{cases} \tag{7}$$

where

$$\bar{\Lambda} = \frac{1}{T}\sum_{q=1}^{T} \Lambda\left(\breve{\boldsymbol{b}}_q^{(y)}\right)$$

$$\sigma_\Lambda = \sqrt{\frac{\sum_{q=1}^{T}\left[\Lambda\left(\breve{\boldsymbol{b}}_q^{(y)}\right) - \bar{\Lambda}\right]^2}{T-1}}. \tag{8}$$

The antipodal bits of the K-bit parent vectors are then exchanged using the so-called *uniform crossover* [15] process, in order to produce two K-bit offspring. Uniform crossover invokes a so-called *crossover mask*, which is a sequence consisting of K randomly generated ones and zeros. Antipodal bits are exchanged between the pair of parents at locations corresponding to a one in the crossover mask. The selection of K-bit parents from the mating pool is repeated, until a new population of P offspring is produced in order to perform the crossover process.

The *mutation* process refers to the alteration of the value of an antipodal bit in the offspring from 1 to -1 or vice versa, with a probability p_m. Finally, under *elitism* [4], we identify the lowest-merit K-bit offspring in the population and replace it with the highest-merit individual from the mating pool. This will ensure that the highest-merit individual is propagated throughout the evolution process.

The GA terminates after $(Y-1)$ number of generations. *The individual corresponding to the highest scalar fitness value in (5) is the detected K number of users' bit vector associated with the bit interval.*

[1]If there is only one nondominated individual in the current population before the termination criteria is met, the next nondominated individuals will be selected, so that there will be more than one individual in the mating pool.

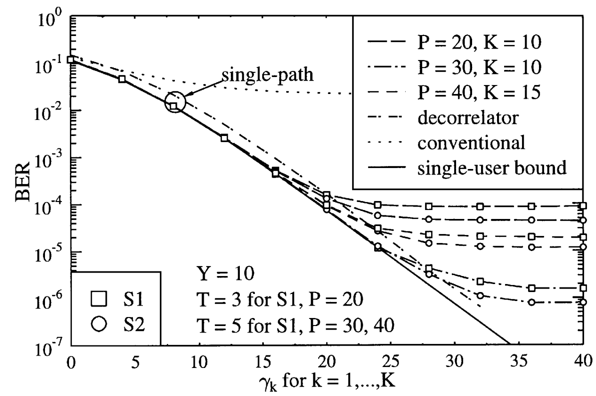

Fig. 2. BER performance of the GA-based multiuser detector employing the individual-selection strategies of S1 and S2 with population sizes of $P = 20, 30, 40$ using binary random signature sequences of length 31 and supporting $K = 10$ and $K = 15$ users. The average received energy at the antennas was assumed to be equal, i.e., $E[\alpha_{k,1}^2] = E[\alpha_{k,2}^2] = 0.5$. The GA parameters used are the probability of mutation specified by $p_m = 0.1$ and $p_m = 0.07$ for $K = 10$ and $K = 15$, respectively, and the evolution was terminated after $Y = 10$ generations.

A. Complexity Issues

Table I compares the computational complexity of our proposed multiuser detector against several conventional multiuser detectors, namely, that of the single-user correlator [12], the decorrelator [1], and the optimum multiuser detector [1], in terms of the number of multiplications and additions required to detect K bits for a single-antenna scenario. The number of computations involved in finding the inverse matrix for the decorrelator is on the order of K^3. In contrast to the decorrelator and the optimum multiuser detector, we can clearly see that the complexity of the GA-based multiuser detector is indirectly related to K. We have seen that our proposed GA-based detector is capable of achieving a near-optimum performance in Fig. 2 up to a certain target bit-error rate (BER), depending on the values of P and Y for a given number of users. Hence, the values of P and Y can be adaptively selected, in order to find a tradeoff between the computational complexity and the performance. Furthermore, the results shown in Table I for the GA-based multiuser detector are based on computing the LLF for every K-bit individual in the population at every generation. Hence, the fitness of some individuals is computed more than once. If the detector has sufficient memory, then these repeated computations can be avoided. Our simulations showed that on average, the total number of LLF computations for a single antenna is $\approx 1/3PY$.

IV. Simulation Results

In this section, computer simulations are presented based on evaluating the BER performance of the GA-based multiuser detector employing the above two GA-based individual-selection strategies highlighted in the previous section. The strategy based on (5), i.e., on the sum of the figures of merit from both antennas, will be denoted as S1, while the strategy based on the Pareto optimality of (6) will be denoted as S2. The processing gain of the signature sequences was $N_c = 31$, and the sequences were randomly generated. Perfect power control and CIR estimation was assumed.

Fig. 2 shows the BER performance against the average signal-to-noise ratio (SNR) $\bar{\gamma}_k$ for the GA-based multiuser detector employing individual-selection strategy S1 and S2 with *equal average received energy at the two antennas,* i.e., for $E[\alpha_{k,1}^2] = E[\alpha_{k,2}^2] = 0.5$. The single-user bound, which assumed equal average received energy at both antennas, was computed using the following equation [12]:

$$P_2 = \left[\frac{1}{2}\left(1 - \sqrt{\frac{\bar{\gamma}_k}{1+\bar{\gamma}_k}}\right)\right]^2 \left(2 + \sqrt{\frac{\bar{\gamma}_k}{1+\bar{\gamma}_k}}\right). \quad (9)$$

For the sake of comparison, the BER performance of a decorrelator and the conventional single-user matched filter is also shown. An error floor is observed for the results shown in the figure. This is due to the limitations of the GA associated with the particular set of P and Y values, not due to the multiple access interference (MAI). It is seen in Fig. 2 that the BER performance for $K = 10$ improved when the population size was increased from $P = 20$ to $P = 30$. However, this also increased the computational complexity. Hence, the value of P can be selected, in order to find a tradeoff between computational complexity and performance. More importantly, we also see from Fig. 2 that the GA employing S2 performs better, exhibiting a lower error floor than S1. Nevertheless, both strategies were capable of matching the single-user bound performance up to $\bar{\gamma}_k = 16$ dB and $\bar{\gamma}_k = 24$ dB for $P = 20$ and $P = 30$, respectively. Furthermore, a gain of about 2 dB can be achieved by the GA-based multiuser detector over the decorrelator, before encountering an error floor. When the number of users is increased, the near-optimum single-user performance can be maintained by increasing the population size P. This is evident in Fig. 2, where a near-optimum performance is maintained up to SNR = 20 dB for $K = 15$, when P is increased to 40. Although not explicitly shown here, we found that a similar performance can be achieved for $K = 10$ when $P = 25$. Reducing P from 40 to 25 resulted in a complexity reduction by a factor of $40/25 = 1.6$, when supporting $K = 10$ users. On the other hand, the complexity of the conventional optimum multiuser detector would be a factor of $2^5 = 32$ higher for $K = 15$ than for $K = 10$.

Fig. 3 shows the BER performance of the proposed detector employing strategy S2 at 20 dB for different number of users K and for different population sizes P. We can clearly see that when K increases, P must be increased in order to maintain near-single-user performance. As seen in Fig. 3, the plateau area at BER of about 10^{-4} is only achieved for sufficiently high P values. Furthermore, the required increase in P is nonlinearly proportional to the increase in K. Nevertheless, the increase in P that led to a higher computational complexity is substantially lower than the exponential increase in the complexity required by the optimum multiuser detector [1].

Finally, the near–far resistence of the GA-based multiuser detector is shown in Fig. 4 in terms of the desired user. The average energy-to-noise ratio $\bar{\gamma}_1$ of the desired user is set to 16 dB, while the energies of all other users were varied in the range of 0–12 dB higher than that of the desired user. We can see that at a population size of $P = 20$, the BER performance

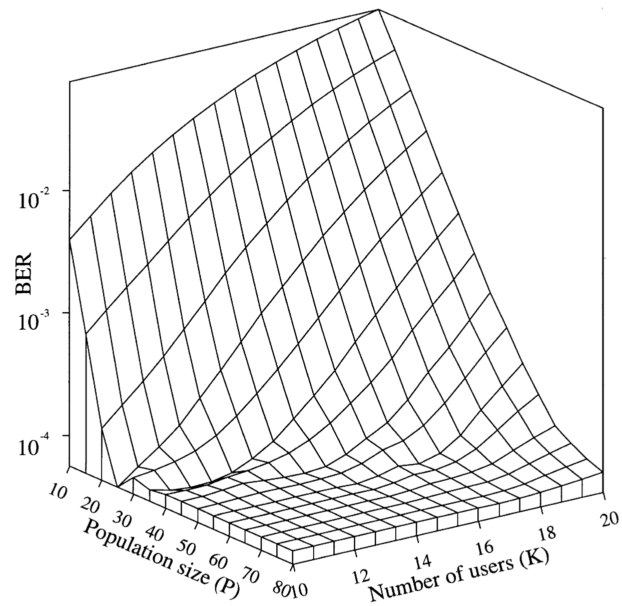

Fig. 3. BER performance of the GA-based multiuser detector employing the individual-selection strategies of S2 with various population sizes and number of users, using binary random signature sequences of length 31. The average received energy at the antennas was assumed to be equal, i.e., $E[\alpha_{k,1}^2] = E[\alpha_{k,2}^2] = 0.5$. The GA parameters used are the probability of mutation specified by $p_m = 0.1$ and the evolution was terminated after $Y = 10$ generations.

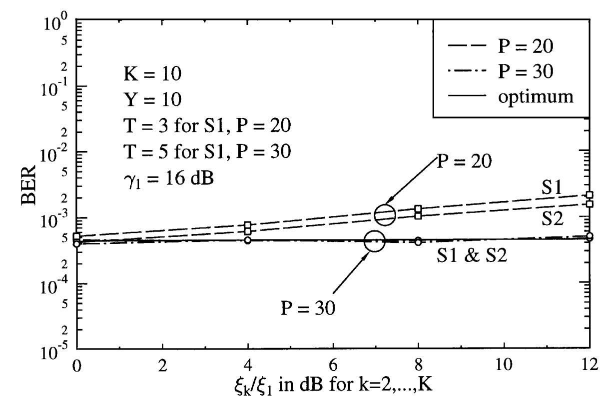

Fig. 4. Relative near–far resistence of the GA-based detector employing individual-selection strategies S1 and S2 with population sizes $P = 20, 30$ using binary random signature sequences of length 31 at $\bar{\gamma}_1 = 16$ dB and supporting $K = 10$ users. The average received energy at the antennas were assumed to be equal. The GA parameters used are the probability of mutation specified by $p_m = 0.1$ and the evolution was terminated after $Y = 10$ generations.

deterioriates slightly, as the interfering users' energy becomes higher relative to the desired user. On the other hand, the BER performance for $P = 30$ remains almost the same, even when the interfering users' energy is 10-dB higher, than that of the reference user.

V. CONCLUSION

In conclusion, we developed a suboptimal multiuser detector based on GAs in order to circumvent the complexity problem faced by the optimum multiuser detector [1]. To mitigate the effects of fading, dual-antenna diversity techniques were used. Two individual-selection strategies were highlighted for the GAs. In our first solution in (5), the mating pool was formed based on the sum of the LLFs derived from the diversity antennas, and we had a fixed mating pool size. According to our second strategy in (6), the LLF statistics were treated independently, in order to select the nondominated individuals to form the mating pool. Hence, the mating pool size was not fixed. We have shown that GAs employing the latter strategy always exhibit a lower BER compared to those employing the former strategy. We have also shown that the BER performance can be improved by increasing the population size. While the complexity of the GA-based multiuser detector is higher than that of the decorrelator used for our comparison, the proposed scheme is capable of achieving a near-optimum performance at a lower complexity as compared to the optimum multiuser detector [1]. Our future work will attempt to extend these advances to a tree search-based multiuser detector, as well as to invoking space–time coding.

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