OPTIMUM MULTIUSER DETECTION IN CDMA USING PARTICLE SWARM ALGORITHM

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ABSTRACT

In this work, a novel optimum multiuser detector (MUD) based on a particle swarm algorithm is presented. The proposed algorithm outperforms the matched filter and the decorrelator multiuser detectors. Moreover, the performance under near–far scenario, the system capacity, and the computational complexity of the proposed detector are also investigated.

Key words: CDMA, multiuser detection, near–far, capacity

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1. INTRODUCTION

Direct sequence code division multiple access (DS–CDMA) [1] provides an attractive alternative to transmitting signals from several users at the same carrier frequency in an uncoordinated manner. However, this code division multiplexing results in multiple access interference (MAI), which if not mitigated can severely degrade the reception quality. In addition, the performance is limited by the presence of the near–far affect.

Several methods have been suggested to reduce the effects of multiple access interference and near-far interference. In [2], an optimal multiuser detector (OMUD) is proposed to mitigate the effect of MAI. Unfortunately, the computational complexity of the OMUD grows exponentially with the number of active users [3]. Since then, emphasis has been placed on the development of suboptimal multiuser detectors, which improve the detection quality under a polynomial complexity [4]. However, there still remains a large gap between the performance of the optimal and that of the suboptimal MUD.

Recently, methods based on heuristic algorithms have been proposed to improve the performance of suboptimal multiuser detectors. They view the MUD problem from a combinatorial optimization point and try to reach the optimal solution iteratively. In [5], genetic algorithms (GA) have been used to solve the MUD optimal detection problem; while in [6] a tabu search (TS) algorithm is proposed.

In this work, a MUD detector based on a discrete version of the particle swarm heuristic [7] is proposed and investigated. The particle swarm optimization (PSO) algorithm shares many basic principles with that of GA. However, when PSO is compared to GA, all the particles in PSO tend to converge to the best solution quickly in most cases with lower computational complexity. Moreover, the PSO is resistant to being trapped in local optima.

2. THE MUD BASED PSO (PS–MUD) ALGORITHM

In synchronous multiuser detection, the received signal in an additive white Gaussian noise (AWGN) channel shared by $K$ users can be expressed by:

$$r(t) = \sum_{k=1}^{K} A_k b_k s_k(t) + z(t)$$  \hspace{1cm} (1)

where $A_k$, $s_k(t)$, and $b_k$ are, respectively, the amplitude, signature code waveform, and bit transmitted by the $k^{th}$ user; $z(t)$ is an additive white Gaussian noise process. The conventional detector for DS–CDMA signals consists of a bank of $K$ correlators (matched filters). The received signal is correlated in branch $k$ ($1 \leq k \leq K$) with its code waveform. The outputs of the matched filters are sampled every symbol to yield soft estimates of the transmitted data. The final binary $(\pm 1)$ received data is obtained by applying a decision rule to the hard limited output according to the sign of the soft estimates.

The outputs of the matched filters, $y_k, k = 1, 2, ..., K$, can be set up into a vector form as [2]:

$$y = R A b + n$$  \hspace{1cm} (2)

where $b = [b_1, b_2, ..., b_K]^T$ is the input vector, $A = \text{diag}(A_1, A_2, ..., A_K)$ is the matrix representing the amplitudes of users’ signals, $R$ is the normalized cross-correlation matrix, and $n$ is the noise vector.

The optimum multiuser detector (OMUD) selects the data sequence $(b_k)$ that maximizes the likelihood function that results in the following detection rule [2]:

$$b = \arg \{ \max_{b \in \{-1,1\}} \exp[-(y - RA b)^T R^{-1}(y - RA b)] \}$$  \hspace{1cm} (3)

The detection rule searches over the $2^K$ possible combinations of the components $b$. In this work, (3) is used as the basic fitness function for the heuristic algorithm, described next, as an approximation to the optimal solution.

The proposed (PS–MUD) algorithm is detailed as follows:

1. Map the output of the matched filter bank from $\{-1,1\}$ to binary $\{0,1\}$ and take it as the initial particle $x_i$. 

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2. Generate the rest of the population, \( \mathbf{x}_i \), \( i = 2, 3, \ldots, PS \) (\( PS \) is the population size), randomly according to the star topology [8].

3. Evaluate the fitness of each particle according to:

\[
 f = 2y^T \mathbf{A}_b - b^T \mathbf{A}_r \mathbf{b}
\]

Find the best performance \( p_g \) in the population and record the best position \( p_i \) along its history.

4. For each bit at the \( d \)th location on the bit-string of particle \( \mathbf{x}_i \), compute its velocity (\( v_{id} \)), defined later, as follow [8]:

\[
v_{id}(l) = v_{id}(l-1) + \phi_1 \cdot \text{rand}_1 \cdot (p_{id} - x_{id}(l-1)) + \phi_2 \cdot \text{rand}_2 \cdot (p_{id} - x_{id}(l-1)) \quad (4)
\]

with \( v_{id} \in \{-v_{\text{max}}, v_{\text{max}} \} \).

5. \( \text{if } \text{rand}_3 < s(v_{id}(l)) \) \( \text{then } x_{id}(l) = 1 \), \( \text{else } x_{id}(l) = 0 \).

6. Go to 3 until the maximum iteration number is reached.

Here \( i \) is the iteration number, \( \text{rand}_i \{1, 2, 3\} \) is a random number generator uniformly distributed in \([0, 1]\), \( s \) is the sigmoid function (\( s(x) = \frac{1}{1 + \exp(-x)} \)), and \( \phi_1 \) and \( \phi_2 \), the acceleration constants, with \( \phi_1 + \phi_2 \leq 4 \) [8], represent the weighting that pull each particle in the direction of \( p_i \) and \( p_g \) positions, respectively. Low values of \( \phi_1 \) and \( \phi_2 \) allow particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past, target region. The velocity \( v_{id} \) will determine the probability threshold to make a choice between 0 and 1. When \( v_{id} \) is high, the individual is more likely to choose 1. The constant parameter \( v_{\text{max}} \) is similar to mutation rate in genetic algorithms. Finally, the second term of (4) can be thought as a cognition part that represents the private thinking of the particle itself and the third term is the social part that represents the degree of collaborations among the particles.

3. SIMULATION RESULTS

A heavily loaded synchronous CDMA system with 20 users operating in an additive white Gaussian noise channel is considered. Gold sequences with a spreading code of length 31 are used. To assess its performance under such a scenario, the PS–MUD algorithm, described here, is used with a population size of 30, a maximum iteration number of 40, \( \phi_1 = \phi_2 = 2 \) and \( v_{\text{max}} = 4.0 \) [7–9]. Binary phase shift keying modulation is employed. Figure 1 depicts the block diagram of the simulated system.

![Figure 1. The MUD detector PSO-based](image-url)
The bit error rate (BER), performance under near–far scenario, the system capacity, and the computational complexity of the proposed detector are used as performance indices. These are detailed next.

3.1. BER Performance of the PS–MUD

A comparison of the BER performance of the PS–MUD with those of the conventional (matched filter) detector (MFDet), the decorrelating detector (DecDet), the branch-and-bound based detector (BnBDet), and the single user bound (SUB) is depicted in Figure 2. It is observed from this figure the excellent improvement in performance brought about by the proposed detector compared to those of the decorrelating detector and the conventional detector. The proposed detector outperforms the matched filter detector by almost 5 dB in order to reach a BER of $10^{-3}$. It can also be seen from this figure the relatively small gap between the BER of the PS–MUD and that of the optimal detector based on branch-and-bound are not too far apart. For instance, at BER=$10^{-4}$ the gap between the two detectors is of approximately 1.7 dB. Moreover, only one update operation, given by (4), is required during each generation which makes the algorithm simple.

![Figure 2. BER for different detectors](image)

![Figure 3. BER of user 2 under near–far scenario](image)
3.1. Near–Far Resistance

The error probability of the desired user is shown in Figure 3 as a function of the interferer signal-to-noise ratio (SNR) ranging from 0 dB to 15 dB. The SNR of the user of interest is set to 8 dB. The considered system is a 2-user CDMA system and the cross-correlation matrix is defined as \( R = \begin{bmatrix} 1 & 0.7 \\ 0.7 & 1 \end{bmatrix} \), which corresponds to a high bandwidth efficiency [10]. From this figure it can be seen that the PS–MUD largely outperforms the conventional detector. It is also shown that the performance behavior of the PS–MUD is consistent with that of the OMUD, which is known to be near–far resistant [2], and it approaches the single user bound as the interferer’s SNR becomes greater than that of the user of interest. Therefore, it can be concluded that the PS–MUD is near–far resistant.

3.3. The System Capacity for the PS–MUD

Figure 4 depicts the BER of the PS–MUD as the number of simultaneous users increases, which gives an idea on the maximum number of users the system can handle without overstepping a tolerable quality of service (QoS). A relative gain of almost seven users for the PS–MUD over the decorrelating detector at BER of \( 10^{-3} \) is gained.

![Figure 4. System capacity of the PS–MUD detector](image)

3.4. The Computational Complexity for the PS–MUD

The computational complexity of a detection scheme used in a system is vital for both implementation and simulation. Figure 5 depicts the computational complexity of the PS–MUD compared with that of the OMUD based on exhaustive search in terms of the average computational time (CPU time).

As can be seen from Figure 5 a remarkable reduction in time complexity of the PS–MUD compared to that of the OMUD takes effect. Using curve fitting techniques, the approximated average time complexity of the two detectors as a function of the number of users \( K \) is roughly equal to \( 0.057 \times K^3 - 3.4 \times K^2 \) for the PS–MUD and \( 0.0012 \times 2^K \) for the OMUD. Hence, it can be seen that the PS–MUD has a linear-like complexity with the number of users, whereas the OMUD based on exhaustive search has an exponential-like complexity with the number of users. This is confirmed by hand calculation of the computational load of the proposed detector in [11], and it is found to be \( \frac{\alpha}{K} (2K^2 + 9K + 2) \) where \( \alpha \) is related to the internal parameters of the algorithm.

4. CONCLUSION

In this work, a MUD detector based on a particle swarm optimization algorithm called particle swarm (PS–MUD) is presented and its performance is evaluated. The PS–MUD outperforms the decorrelator detector and the matched filter detector and presents very interesting results. In addition to being inherently near-far resistant it is also resulting in a higher capacity compared to the decorrelating detector. Finally, the computational complexity of the PS–MUD is far less than that of the OMUD; specifically, it is negligible for high numbers of users compared to that of the OMUD.
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