Particle Swarm Optimization for Multiuser Asynchronous CDMA Detector in Multipath Fading Channel

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Abstract- A multiuser detector for direct-sequence code-division multiple-access systems based on particle swarm optimization (PSO) algorithm is proposed. To work around potentially computational intractability, the proposed scheme exploits heuristics in consideration of both global and local exploration maximum likelihood (ML). Computer simulation demonstrates that the proposed detector offers near-optimal performance with considerably reduced computation complexity compared with that of existing sub-optimum detectors are presented.

Key Words-- Code-division multiple access, particle swarm optimization, evolutionary algorithm, multiuser detection.

1 Introduction

Recently, direct-sequence code division multiple access (DS-CDMA) systems has become very popular various applications such wireless in as communications [1-2]. However, Multiple-access interference (MAI) and near-far are a major limiting factor conventional direct-sequence code division multiple access systems. As an efficient way to mitigate the effect of MAI, various multiuser detection methods have been proposed [2-9]. The optimum multiuser detector (OMD) was developed by Verdú [3] for asynchronous CDMA system. Also, Verdú has shown that optimum, near-far resistant multiuser demodulation can be achieved via the maximization of an integer quadratic objective function. Unfortunately, the computation complexity of OMD increases exponentially with the number of users that causes the implementation of OMD of impractical [2]. Therefore, researchers have devoted themselves to finding suboptimum detectors that can achieve better performance with less computation complexity. Hence, the implementation complexity of even suboptimal multi-user detectors such as the

decorrelator [4-5] and multistage interference cancellation [6-9] has so far prevented their widespread acceptance in industry.

Due to the computational complexity of the problem, heuristics have been proposed recently, including genetic algorithm (GA) [10-13], local search algorithm [14], evolutionary programming (EP) [15] based optimal multiuser detector have been utilized to solve the multiuser detection (MUD) problem. Other Evolution methods such Hybrid artificial Neural Network for wafer lot output time prediction [25]. immune algorithm for satellite-derived land-cover classification [26] and evolution method for mobile networks [27] problem. GA has been highly successful and widely implemented within the CDMA Systems. For instance, Ergün et al. [10] utilized the GA as the first stage of a multistage multiuser detector, in order to provide good initial guesses for the subsequent stages. K. Yen et al. [11] a hybrid detector employs GA based scheme in conjunction with a local search in order to improve the initial guesses. Abediet et al. [13] developed a hybrid detector for a CDMA system. The

aim is to improve the structure of detector, which results to better estimation of the data bits. As GA required the process of initialization, the first estimation of the tap coefficients performance that forms the first generation of GA. Unfortunately, the flaws of GAs are slow convergence to a good near-optimum and high computational complexity. Driven by the demand for the algorithms with significantly lower computational complexity than the optimum algorithm but slightly worse performance, this work proposes a novel approach to solve the problem of multiuser detection in asynchronous CDMA systems.

A new evolutionary computation technique, call particle swarm optimization (PSO) [17-19], has recently been proposed, and has proven to be a powerful optimization approach. We have found that using a conventional detector (CD) to produce initial values for the proposed PSO works very well. This choice retains the advantage of linear computational complexity. Further, in each case tested, this initialization method produced a final solution with performance very close to optimum. Since each iteration will always improve performance, convergence of our algorithm is guaranteed. This property ensures PSO to be less susceptible to getting trapped on local minima. Moreover, the PSO requiring only velocity calculation clearly has advantages of algorithmic simplicity and lower computation load owing to that the three major operations of select, crossover, and mutation used in a GA are not necessary for the PSO. These operations always result in complexity and difficulty of program implementation. Furthermore, to overcome the problem of premature convergence, instead of using the mutation operator in a GA, the PSO applies the method of the controlling the balance of particle's velocity between local and global best positions in the problem space. Hung et al. [20-21] [25], Soo et al. [22] and Liu et al. [23] demonstrate that a PSO-based MUD for synchronous and Asynchronous CDMA (ACDMA) provides optimal BER performance with a lower computation complexity than a GA-based MUD.

This paper is organized as follows. In Section 2 we will describe the ACDMA system along with the multipath channel. Section 3 describes the PSO used to implement our proposed detector. In Section 4, we will present some simulation results, which demonstrate the potential of the proposed joint detector scheme. Finally, Section 5 is the concluding section.

2 System Model

Consider an asynchronous CDMA system accommodating K users. Let r(t), the signal at the receiver, is the superposition of K transmitted signals in addition to channel noise when there are K active transmitters in asynchronous Gaussian channel in given time interval, as shown by

$$r(t) = \sum_{i=-P}^{P} \sum_{k=1}^{K} \sqrt{A_{k}(i)} \ b_{k}(i) \ s_{k}(t-iT - \tau_{k}) + n(t), \ t \in \mathbb{R}$$
(1)

where $\sqrt{A_k(i)}$ is the power of the *k*th user at time *iT*, 1/T is the data rate, $b_k(i) \in \{-1,1\}$ is the *i*th transmitted bit of the kth user, $s_k(t)$ represent the kth user's transmitted waveform which is the time-limited wide-band signal derived from the signature sequence, the length of which is N and $N = T/T_c$, where T and T_c , represent the symbol duration and the chip of signatures sequence, assigned to that packet in the spread spectrum CDMA system, respectively, $\tau_k \in [0,T)$ is the transmission delay of the kth user relative time and 2P + 1 is the packet size and n(t)represents the additive white Gaussian noise with two-sided power spectral density $N_0/2$. Without generality, we loss of can assume that $0 \leq \tau_1 \leq \tau_2 \leq \cdots \leq \tau_K < T_b$. The received signal amplitude and the transmission delays τ_k are assumed to be known at the receiver.

In ACDMA systems, the CD consists of a bank of filters matched to the signature waveforms of each user, and a simple thresholding device that produces an estimate \hat{b}_{ik} for the *i* th information bit of the *k* th user based on the sign of the *i* th output of the *k* th matched filter

$$y_{k}^{i} = \int_{iT - \tau_{k}}^{(i+1)T - \tau_{k}} r(t) s_{k} (t - iT - \tau_{k}) dt$$
$$\mathbf{b}_{CD}^{i} = sign(\mathbf{y}^{i}) \tag{2}$$

where $\mathbf{y}^{i} = \begin{bmatrix} y_{1}^{i} & y_{2}^{i} & \cdots & y_{K-1}^{i} \end{bmatrix}^{T}$. The sufficient statistics for demodulation of the transmitted bits **b** given by the *NK* matched outputs. The matrix form of the outputs of matched filters can be expressed as

 $\mathbf{Y} = \mathbf{R}\mathbf{A}\mathbf{b} + \mathbf{n}$, where

$$\mathbf{Y} = [\mathbf{Y}^{\mathrm{T}}(-P), \cdots, \mathbf{Y}^{\mathrm{T}}(P)]^{T}, \mathbf{Y}(i) = [\mathbf{Y}_{1}(i), \cdots, \mathbf{Y}_{k}(i)]^{\mathrm{T}},$$

$$\mathbf{A} = diag(\mathbf{A}(-P), \cdots, \mathbf{A}(P)),$$

$$\mathbf{A}(i) = diag(\sqrt{A_{1}(i)}, \cdots, \sqrt{A_{k}(i)}) \text{ is a diagonal}$$

(3)

matrix whose diagonal elements are the signal power of the corresponding users; $\mathbf{b} = \begin{bmatrix} \mathbf{b}^{\mathrm{T}}(-P), \cdots \mathbf{b}^{\mathrm{T}}(P) \end{bmatrix}^{\mathrm{T}}$, $\mathbf{b}(i) = \begin{bmatrix} b_{1}(i), \cdots b_{k}(i) \end{bmatrix}^{\mathrm{T}}$, and **n** is a Gaussian noise vector with covariance matrix power spectral density $N_{0}\mathbf{R}$. The matrix **R** can be written as [10-11], [24]

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}(0) & \mathbf{R}^{\mathrm{T}}(1) & 0 & \cdots & 0 \\ \mathbf{R}(1) & \mathbf{R}(0) & \mathbf{R}^{\mathrm{T}}(1) & & \vdots \\ 0 & \mathbf{R}(1) & \mathbf{R}(0) & \ddots & 0 \\ \vdots & \vdots & \vdots & \ddots & \mathbf{R}^{\mathrm{T}}(1) \\ 0 & \cdots & 0 & \mathbf{R}(1) & \mathbf{R}(0) \end{bmatrix}$$
(4)

where $\mathbf{R}(0)$ is a $K \times K$ matrix whose elements are given by

$$R_{jk(0)} = \begin{cases} 1, & \text{if } j = k \\ \alpha_{jk}, & \text{if } j < k \\ \alpha_{kj}, & \text{if } j > k \end{cases}$$
(5)

and $\mathbf{R}(1)$ is a $K \times K$ matrix whose elements are given by

$$R_{jk(1)} = \begin{cases} 0, & \text{if } j \ge k \\ \alpha_{kj}, & \text{if } j < k \end{cases}$$
(6)

 α_{jk} denotes the partial crosscorrelation function for the *j*th and *k*th user .

For asynchronous CDMA the optimum multiuser detection [2-3] can be expressed as

$$\hat{\mathbf{b}}_{OMD} = \arg\{\max_{\mathbf{b} \in \{+1,-1\}^{(2P+1)K}} 2\mathbf{y}^T \mathbf{A} \mathbf{b} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}\}.$$
 (7)

Let **H=ARA**, the OMD problem is equivalent to maximizing an objection

$$L(\mathbf{b}) = 2\mathbf{y}^T \mathbf{A}\mathbf{b} \cdot \mathbf{b}^T \mathbf{H}\mathbf{b}$$
(8)

with the information bits vector **b** constrained to the set $\{1, -1\}^{(2P+1)K}$. The optimal multiuser detection is an NP-complete combinatorial optimization problem is inefficient for its solution. When the frequency selective fading occurs, the discrete received signal for the *k*th user at the conventional receiver is given by

$$r(t) = \sum_{i=-P}^{P} \sum_{k=1}^{K} \sqrt{A_k(i)} \ b_k(i) \ s_k(t - iT - \tau_{k,l}) * h_k(t) + n(t),$$
(9)

where the symbol * denotes convolution, $h_k(t) = \sum_{l=1}^{L} c_{k,l} e^{-j\varphi_{k,l}} \alpha(t - \tau_{k,l})$ is the baseband impulse

response of channel for user k. $c_{k,l}$ is the amplitude of the *l*th path of the *k*th user channel which has Rayleigh

distribution, $\varphi_{k,l}$ and $\tau_{k,l}$ are the analogous phase and delay that have uniform distributions in the intervals [0, 2 π] and [0, T], respectively. The output of the filter matched to the *l*th path of user *k* at time *i*T is obtained as

$$y_{k,l}^{i} = \int_{iT + \tau_{k,l}}^{(i+1)T + \tau_{k,l}} r(t) s_{k} (t - iT - \tau_{k,l}) dt$$
(10)

The output of matched filter can be expressed in the matrix form as

$$\mathbf{Y} = \mathbf{R}\mathbf{A}\mathbf{W}\mathbf{b} + \mathbf{n} \tag{11}$$

where

$$\mathbf{Y} = (\mathbf{Y}(-P), \cdots \mathbf{Y}(i), \cdots, \mathbf{Y}(P))$$

$$\mathbf{Y}(i) = (\mathbf{Y}_{1}(i), \cdots, \mathbf{Y}_{k}(i))$$

$$Y_{k}(i) = (Y_{k,1}(i), \cdots Y_{k,L}(i))$$

(12)

 $\mathbf{Y}(i)$ is the output all K users matched filters, $\mathbf{Y}_k(i)$ is the outputs of the *k*th users matched filters at time *iT*, and **W** is the matrix of received signal coefficients for all *K* users definded as

$$\mathbf{W} = diag(\mathbf{W}(-P), \cdots, \mathbf{W}(P))$$
$$\mathbf{W}(i) = diag(\beta_1(i)I, \cdots, \beta_K(i)I)$$
$$\beta_k(i) = \left[\beta_{k,1}(i), \cdots, \beta_{K,K}(i)\right]^T$$
(13)

where I is an $L \times L$ identity matrix, $\beta_{k,l} = c_{k,l}e^{-j\varphi_{k,l}}$, and R is the correlation matrix as

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}(0) & \cdots & \mathbf{R}(2P) \\ \vdots & \ddots & \vdots \\ \mathbf{R}(-2P) & \cdots & \mathbf{R}(0) \end{bmatrix}$$

$$\mathbf{R}(i) = \begin{bmatrix} \mathbf{R}_{1,1}(i) & \cdots & \mathbf{R}_{1,K}(i) \\ \vdots & \ddots & \vdots \\ \mathbf{R}_{K,1}(i) & \cdots & \mathbf{R}_{K,K}(i) \end{bmatrix}$$
(14)

The conventional single user detector is Rake receiver that combines the outputs of matched filter using the maximum ratio combining method.

$$Y_{rake_k} = \operatorname{Re}\left\{\sum_{l=1}^{L} \beta_{k,l}^* Y_{k,l}\right\}$$
(15)

3 Particle swarm optimization based multiuser detector

PSO is an evolutionary computation technique through individual improvement plus population cooperation and competition, which is based on the simulation of simplified social models, such as bird flocking, fish schooling, and the swarming theory [18]. One advantage of PSO over the GA is its algorithmic simplicity. A GA comprises parameters of its major operators which are crossover, mutation, and elitism. The parameters are population size, probability of mutation, probability of crossover and selection. However, there PSO has one simple operator, velocity calculation. The benefit of a small number of operators is the reduction of computation and the elimination of the need to select the best operator for a given optimization. Another difference between the PSO and GA is the ability to control convergence. Mutation and crossover rates can subtly affect the convergence of the GA, but not an effectively as the inertial weight. D .B. Fogle [16] indicated that the decrease of inertial weight significantly increases the swarm's convergence. This type of control allows the use to determine the rate of convergence, and the final level of stagnation ultimately achieved. Stagnation occurs in the GA when eventually all the individuals possess primarily the same genetic code. In that case, the gene pool is so homogeneous that crossover has little or no effect, and each successive generation is the same as the first. However, this effect can be controlled or prevented in the PSO. With a large inertial weight the particles continue to fly back and forth over the global best, and new locations of higher fitness can be identified. Form the above and the NP-complete nature of the problem of MUD, applying PSO to the problem of MUD can be justified.



Fig. 1 PSO based multiuser detection scheme with the discrete-time equivalent models.

A novel low-complexity multiuser detector for ACDMA systems by applying the PSO technique is presented in this section. Basically, the PSO based multiuser detector is shown in Fig. 1. In this context, the population is called a *swarm* and the individuals are called *particles*. Resembling the social behavior of a swarm of bees to search the location with the most flowers in a field, the optimization procedure of PSO is based on a population of particles which fly in the solution space with velocity dynamically adjusted according to its own flying experience and the flying experience of the best among the swarm. Fig. 2 shows the flow chart of a PSO algorithm. During the PSO process, each potential solution is represented as a particle with a position vector and a moving velocity represented as **x** and **v**, respectively.

Thus for a *K*-dimensional optimization, the position and velocity of the *i*th particle is represented as $\mathbf{x}_i = (x_{i,1}, x_{i,2}, ..., x_{i,K})$ (i.e., the output data of CD receiver $\hat{b}_i = [\hat{b}_{i,1}, \hat{b}_{i,2}, \cdots, \hat{b}_{i,K}]$) and $\mathbf{v}_i = (v_{i,1}, v_{i,2}, ..., v_{i,K})$. The randomness enables the exploration of a broad population of possible solutions in the antire search space. At every time step

exploration of a broad population of possible solutions in the entire search space. At every time step, an associated value for each particle is evaluated according to with a function called the *cost function*, which is critically defined and configured by considering the search objective with x_i as input. The value normally called the *cost* indicates the goodness of the solution. However, a practical implementation has not only one possible fitness function that can reflect the design objective. A function that can best represent the relative importance of each goal can often be obtained through trial and error.

The position of the individual best fitness achieved by particle *i* has achieved so far. Meanwhile, that of the highest fitness which has been obtained among all the particles in the population so far, are called the personal best (*pbest* denoted as \mathbf{x}_{i}^{best}) and the global best (*gbest* denoted as \mathbf{x}^{best}), respectively, and both are stored to generate the new velocity of particle *i*. Each particle adjusts its velocity during the process according to its own experience and the position of the best of all particles to move toward the best solution. Meanwhile, a condition is also set during the following step, controlling the algorithm when it stops by either setting it to obtain an acceptable target solution or to run for a set maximum number of search iterations. If the algorithm does not step, after a time step, Δt , then the new velocity $\mathbf{v}_i(t + \Delta t)$ for particle *i* is updated by

$$\mathbf{v}_{i}(t + \Delta t) = w \cdot v_{i}(t) + c_{1} * r_{1} * (\mathbf{x}_{i}^{best}(t) - \mathbf{x}_{i}(t)) + c_{2} * r_{2} * (\mathbf{x}^{best}(t) - \mathbf{x}_{i}(t))$$
(16)

where $v_i(t)$ is the old velocity of the particle *i* at time *t*. Apparent from this equation, the new velocity is related to the old velocity weighted by w and also associated to the position of the particle itself and that of the global best one by factors c_1 and c_2 . The c_1 and c_2 are therefore referred to as the cognitive and social rates, respectively, because they represent the weighting of the acceleration terms that pull the individual particle toward the personal best and global best positions. The inertia weight w in (16) is employed to manipulate the impact of the previous history of velocities on the current velocity. Therefore, w resolves the tradeoff between the global and local exploration ability of the swarm. Large inertia weights encourage global exploration, while a small one promotes local exploration, i.e., fine-tuning the current search area. For the purpose of intending to simulate the slight unpredictable component of natural swarm behavior, two random functions r_1 and r_2 are applied to independently provide uniform distributed numbers in the rang [0,1] to stochastically vary the relative pull of the personal and global best particles. The new position for particle *i* is determined from the updated velocities the following equation:

$$\mathbf{x}_{i}(t + \Delta t) = \mathbf{x}_{i}(t) + \Delta t * \mathbf{v}_{i}(t + \Delta t)$$
(17)

The populations of particles are then moved according to the new velocities and locations obtained with (16) and (17), and tend to cluster together from different directions. The evaluation of each associate fitness of the new population of particles is thus repeated. The algorithm runs iteratively through these processes until it stops. Each particle is an m-dimensional real-valued vector, where m is the number of optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space. For this paper, a population size of 30 particles is selected and randomly generated initially. This number is suggested for most engineering problem and has also been shown to be sufficient for our problems [17].

As shown in Equation (16), the second term $c_1 \cdot r_1 \cdot (\mathbf{x}_i^{best}(t) - \mathbf{x}_i(t))$ in the velocity updating rule approaches zero if particle $\mathbf{x}_i(t)$ lies close to the local best $\mathbf{x}_i^{best}(t)$. Similarly, the third term $c_2 \cdot r_2 \cdot (\mathbf{x}^{best}(t) - \mathbf{x}_i(t))$ in the velocity updating rule approaches zero for particles $\mathbf{x}_i(t)$ lying close to their global best $\mathbf{x}^{best}(t)$. It suffices to say that particles close to their local best $\mathbf{x}_i^{best}(t)$ or global

best $\mathbf{x}^{best}(t)$ evolve in a much refined way in comparison to those far away from their best ones. There is no guarantee, however, that these particles close to their best positions so far will converge to the desired optima. That is, these particles might unfortunately converge to local optimum, which is called a premature phenomenon. To solve this problem, conventional techniques generally randomly initialized a portion of particles in the swarm after generating the global best $\mathbf{x}^{best}(t)$ to improve the convergence rate. Alternatively, velocities of factors within each particle are slightly adjusted at random during each iteration. This technique, however, required that empirically derived parameters be used, which does not apply well to every objective functions under consideration. To maintain the simple structure of conventional PSO while avoiding evolution of all particles toward a unilateral direction, a preferential velocity-updating mechanism is proposed and incorporated into the PSO to avoid premature of evolution in this paper. The evolution is directed in such a way that particles with coarse evolutionary resolution (i.e., particles far away from $\mathbf{x}^{best}(t)$) are provided with more spontaneity to search by imposing heavier preference on the second term and lighter preference on the third term of the velocity-updating rule in Equation (16). On the other hand, particles with finer evolutionary resolution (i.e., particles close to $\mathbf{x}^{best}(t)$) are provided with better exploitation capability to search toward $\mathbf{x}^{best}(t)$ by imposing lighter preference on the second term and heavier preference on the third term of the velocity-updating rule.

To achieve the above-mentioned objective, a preference function denoted as $PF_i(t)$ is incorporated into Equation (16) for particle *i*, forming the proposed velocity-updating rule as follows:

$$\mathbf{v}_{i}(t+\Delta t) = w \cdot \mathbf{v}_{i}(t) + c_{1} \cdot r_{1} \cdot \left[\mathbf{x}_{i}^{best}(t) - \mathbf{x}_{i}(t)\right]$$

$$\cdot PF_{i}(t) + c_{2} \cdot r_{2} \cdot \left[\mathbf{x}^{best}(t) - \mathbf{x}_{i}(t)\right] \cdot \left[1 - PF_{i}(t)\right]$$
(18).

For clarity, the steps to calculate the preference function $PF_i(t)$ are summarized below:

Step 1: Calculate distance deviated from $\mathbf{x}^{best}(t)$ for every particle *i* in the swarm:

$$\boldsymbol{d}_{i} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{i}(t) \right\|_{2}^{2}, \tag{19}$$

Step2: Sort $\{d_i, i = 1, 2, \dots, Q\}$ in ascending order to obtain the index of the results:

$$\mathbf{k} = \underset{i}{Arg} \quad sort_{ascending} \left\{ d_1 \quad d_2 \quad \cdots \quad d_i \quad \cdots \quad d_Q \right\} (20)$$

where
$$\mathbf{k} = \left[k_1 \quad k_2 \quad \cdots \quad k_i \quad \cdots \quad k_Q \right].$$

Step 3: Calculate $PF_i(t)$ for every particle *i* in the swarm of *Q* particles:

$$PF_i(t) = \frac{k_i}{Q},\tag{21}$$

To better understand the derivation of $PF_i(t)$, a swarm of 5 particles each comprising 2 factors is illustrated below:

Example: Assume a swarm $\{\mathbf{x}_i(t), i = 1, 2, \dots, 5\} = \{(1,1) \ (2,2) \ (3,3) \ (4,4) \ (5,5)\}$, where the global best position $\mathbf{x}^{best}(t) = (2.2, 2.3)$ is know as a priori. We calculate $PF_i(t)$ via the steps mentioned earlier. Step 1:

$$d_{1} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{1}(t) \right\|_{2}^{2} = \left\| (2.2,2.3) - (1,1) \right\|_{2}^{2} = 3.13$$

$$d_{2} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{2}(t) \right\|_{2}^{2} = \left\| (2.2,2.3) - (2,2) \right\|_{2}^{2} = 0.13$$

$$d_{3} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{3}(t) \right\|_{2}^{2} = \left\| (2.2,2.3) - (3,3) \right\|_{2}^{2} = 1.13$$

$$d_{4} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{4}(t) \right\|_{2}^{2} = \left\| (2.2,2.3) - (4,4) \right\|_{2}^{2} = 6.13$$

$$d_{5} = \left\| \mathbf{x}^{best}(t) - \mathbf{x}_{5}(t) \right\|_{2}^{2} = \left\| (2.2,2.3) - (5,5) \right\|_{2}^{2} = 15.13$$

Step 2: Sort

$$\begin{cases} d_1 & d_2 & d_3 & d_4 & d_5 \end{cases}$$

= {3.13 0.13 1.13 6.13 15.13}

in ascending order into $\{0.13 \ 1.13 \ 3.13 \ 6.13 \ 15.13\}$

 $= \left\{ d_2 \quad d_3 \quad d_1 \quad d_4 \quad d_5 \right\}$

where the indices associated with the sorted results becomes

 $\{k_1 \ k_2 \ k_3 \ k_4 \ k_5\} == \{3 \ 1 \ 2 \ 4 \ 5\}.$ Step 3:

$$PF_{1}(t) = \frac{k_{1}}{5} = \frac{3}{5} = 0.6$$

$$PF_{2}(t) = \frac{k_{2}}{5} = \frac{1}{5} = 0.2$$

$$PF_{3}(t) = \frac{k_{3}}{5} = \frac{2}{5} = 0.4$$
$$PF_{4}(t) = \frac{k_{4}}{5} = \frac{4}{5} = 0.8$$
$$PF_{5}(t) = \frac{k_{5}}{5} = \frac{5}{5} = 1.0.$$

;

As demonstrated in this example, particle $\mathbf{x}_{2}(t)$ lies most close to the global best position $\mathbf{x}^{best}(t)$. No emphasis on spontaneity is required in this case. As a result, a lighter weighting of $PF_2(t) = 0.2$ is multiplied with the second term and a heavier weighting of $1 - PF_2(t) = 0.8$ is multiplied with the third term of the velocity-updating rule in Equation (18) to provide a finer tuning of evolution toward the trajectory of $\mathbf{x}^{best}(t)$. On the contrary, $\mathbf{x}_{5}(t)$ far away from the global best $\mathbf{x}^{best}(t)$ should focus on more spontaneous evolution irrelevant to the global best $\mathbf{x}^{best}(t)$ to provide better exploration capability in searching for the solutions. As a result, a heavier weighting of $PF_5(t) = 1.0$ is multiplied with the second term and a zero weighting of $1 - PF_5(t) = 0$ is multiplied with the third term of the velocity-updating rule in Equation (18), in an attempt to avoid premature convergence of the swarm toward a local optimum.

The above-mentioned technique where the preference function $PF_i(t)$ for the swarm of Q particles has discrete values uniformly distributed between 1/Q and 1, i.e., $\{1/Q, 2/Q, \dots, 1\}$ as shown in Equation (21), is called discrete preferential velocity-updating PSO. In addition to this technique, we have also developed another variant called continuous preferential velocity-updating PSO, in which the preferential function $PF_i(t)$ is defined as:

$$PF_i(t) = \frac{d_i(t)}{\sum_{i=1}^{Q} d_i(t)}.$$
(22)

Note that $PF_i(t)$ functioning in a continuous mode in Equation (22) has arbitrary values anywhere between 0 and 1.

The PSO technique based multiuser detection can be described in the following steps.

Step 1. Solution Representation: The multiuser detection can be regarded as an optimization problem that finds the most likely combination of binary

transmitted bits $\hat{\mathbf{b}}_{OMP, p}$. The configuration of the trial

solution $[\hat{b}_{1,p}, \hat{b}_{2,p}, \dots, \hat{b}_{K,p}]$ is already an antipodal binary string of length *K*; therefore, the encoding process is unnecessary.

Step 2: Initialization: A particle set with P_p members named the *swarms population* is created each time when the PSO is performed and used to improve solutions generated with PSO operations. P_p

is known as the *population size*. A larger the population size leads to a faster the convergence rate but companying a higher computational complexity. In this study, the CD creates the seed swarm in the initial population.

Step 3: Evaluate the fitness values of all particles. Let *pbest* of each particle and its objective value equal to its current position and objective value, and *gbest* and its objective value equal to the position and objective value of the best initial particle.

Step 4: Update the velocity and position of each particle according to Equations (17) and (18).

Step 5: Evaluate the objective values of all particles according to Equation (7). The system aims to find the

b with the minimum cost. Consequently, the cost function of a swarm for the duration of bit i is defined Equation (7)

Step 6: For each particle, compare its current objective value with the object value of its *pbest*. If current value is better, then update pest and its object value with the current position and objective value. Furthermore, determine the best particle of current warm with the best objective values. If the objective value is better than the object value of *gbest*, then update *gbest* and its objective value with the position and objective value of the current best particle.

Step 7: Termination criteria: If a predefined stopping criterion is met, then output *gbest* and its objective value; otherwise go back to Step 4.



Fig. 2 MPSO algorithms Flowchart.

4 Numerical Results and Discussions

This section presents some sample numerical results which illustrate the potential of using the proposed method as an effective tool for improving the performance of ACDMA communications over multipath fading channel. In the computer simulation, the performance of proposed the PSO detector was compared with the CD and GA-based MUDs. The first 10 user examples use randomly generated gold codes with length 31 as the signature sequences and perfect channel knowledge at the receiver.

Fig. 3 depicts the BER performance and the effects of evolution in terms of number of generations for various population sizes *P* for *K*=10. The optimum performance of the multiuser detector utilizing an exhaustive search for *K*=10 is also shown. In this case, the optimum multiuser detector has to compute the cost function of Equation (7) $2^{10} = 1024$ times, which corresponds to every possible combination of *b*.



Fig. 3 The BER of the PSO based multiuser detectors in the perfect power control system with SNR = 7 dB, K=10 users.

Upon observing Fig. 3, we notice that the PSO-assisted multiuser detector is capable of reaching a near-optimum BER performance with G=30generations with the aid a population size of P=30 for K=10 users over an AWGN channel at an SNR of 10 dB. This constitutes a total of $P \times G=900$ number of correlation metric evaluations according to Equation (7). In fact, this number was derived based on the fact that cost value is calculated for every individual in the population at every generation. However, in reality, certain individuals will reappear over the course of the evolution. Hence, the cost values of these individuals need not be recalculated, because they are stored in the memory. Furthermore, the implementation of our proposed PSO-assisted multiuser detector is feasible in practical terms and offers an alternative to the implementation of the optimum multiuser detector.

Fig. 4 illustrates the performance of the proposed PSO based detector over a flat Rayleigh fading channel with K=20 users. For comparison, the figure reveals that the proposed detector can achieve near single-user performance. The performances of the CD, GA-based MUDs [10] are included to show the gap in performance. Fig. 4 illustrates the case in [10] where the GA is invoked only for bit estimation and coefficients are assumed to be known at the receiver, and the population size and the number of generations are P=50 and G=50, respectively. The PSO need P=30 and G=50 for the same performance, thus 2500/1500 saving in the computational complexity.



Fig. 4 BER versus SNR performance comparison between CD, GA, GA-ML and PSO-ML for asynchronous system over a Flat fading channel with K=20.

One major reason for using PSO based on MUD is to overcome the detrimental effects of the near-far problem and relax the stringent power control requirement. To investigate the near-far immunity of the proposed detector, we consider an ACDMA system over a flat fading channel with the desired user being interfered by other equal power users. We can see that the conventional receiver is quite sensitive to the near-far problem, and its performance degrades significantly when the interfering signal strength increases. For our proposed detector, however, its performance actually can become better when the interfering signal strength increases. Fig. 5 illustrates the near-far immunity of PSO based MUD.



Fig. 5 Near-far immunity of PSO based MUD.



Fig. 6 BER of PSO-ML, GA and GA-ML in a multiuser system over a two-path Rayleigh fading channel (perfect channel estimation, SNR=20)

Fig. 6 depicts the BER performance of the different schemes in a multiuser system with SNR=20dB over a two-path Rayleigh fading channel versus the number of users. It shows that in the presence of multiple users, the PSO-ML detector still outperforms the detector GA and GA-ML detector. It is clear from the figures that a possible explanation for this is that when K becomes large, the MAI also increases and thus conventional detector provides poor performance in the present of large number of active users. However, the proposed detectors can achieved an acceptable BER in spite of the increasing number of active users.



Fig. 7 BER versus SNR performance comparison between Rake Receiver, GA, GA-ML and PSO-based ML for asynchronous system over a two path fading channel with K=10

In this case, we have found that using a MRC receiver to produce initial values for the proposed PSO algorithm works very well. In Fig. 7, we plot the analytical and simulation results on the BER of the Rake receiver and GA in a multiuser system over a two-path Rayleigh fading channel [12],[23] We observe that the performance of our algorithm is better

than of all existing suboptimum schemes with same level of complexity. Since the proposed detector can efficiently cancel the MAI and ISI in multipath fading channel, the transmission capability of the ACDMA will be considerably increased.

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5 Conclusions

This paper presents a particle swarm scheme to decide the transmitted bits of a multiuser detector in asynchronous CDMA communication system. To work around potentially computational intractability, the proposed scheme exploits heuristics in consideration of both global and local exploration likelihoods. Finally, it has been shown that the proposed can alleviate the effects of the near-far problem and significant system capacity improvement can be achieved using the proposed detector instead of the conventional DS/CDMA receiver.

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