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Particle-Swarm-Optimization-Based Multiuser Detector for Multicarrier CDMA Communications

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***Abstract*—Multi-carrier code division multiple access (MC-CDMA) mobile communication systems targets to overcome the multi-path fading influences and to increase system capacity. In this paper, we present a modified version of evolutionary algorithm, called as Particle swarm optimization (PSO) which quickly converges to global optimal solution. This algorithm is used to develop a suboptimal multi-user detection (MUD) strategy for MC-CDMA systems. More specifically, after getting the initial population from the front-end frequency domain maximal ratio combining (MRC) or minimum mean-square error (MMSE) equalizer, simplified PSO optimization is applied. Simulation results show that the proposed PSO algorithm remarkably improves the performance of both, MRC and MMSE detector. Results of proposed MMSE-PSO scheme are better than the MMSE detector and it also outperforms MRC-PSO scheme.**

Keywords-Particle Swarm Optimization (PSO), Multiuser Detection (MUD), Multi-carrier Code Division Multiple Access (MC-CDMA)

I. INTRODUCTION

Multicarrier CDMA emerged from the combination of direct sequence CDMA (DSCDMA) and orthogonal frequency division multiplexing (OFDM) technologies [1]. While in DS-CDMA the spreading spectrum takes place in the time domain, in the classic MC-CDMA, the spreading is done in the frequency domain. Hence, the detector has the capacity to achieve frequency diversity at the cost of a reduced spreading factor. A modified MC-CDMA system that employs both time and frequency spreading is proposed in [2]. However, the code orthogonally among users in MC-CDMA systems is highly distorted by the instantaneous frequency response of the channel. Therefore, the multiple access interference (MAI) caused by the frequency selectivity in fading channels degrades the performance of MC-CDMA communication systems.

Multiuser detection (MUD) is a well known alternative to mitigate the MAI in a CDMA system [3], [4]. The best performance is acquired by the optimum MUD, based on the log-likelihood function (LLF) [3]. However, this is achieved at the cost of huge computational complexity, which increases exponentially with the number of users. In the last decade, a variety of multiuser detectors with low complexity and sub-optimum performance were proposed, such as linear detectors [3], subtractive interference canceling [4], semidefinite programming approach by using interior-point methods and heuristic methods. The last three methods have been used for solving different detection models and obtaining near-maximum likelihood (near-ML) performance at cost of polynomial computational complexity A large amount of MUD researches have focused on the complexity problem. Two quite different, suboptimal approaches for MUD emerged, and they had been proved to have much lower complexity than the optimum multi-user detector: interference cancellation (IC) and adaptive filtering. The minimum mean square error (MMSE) multi-user detection is described in [5], [6], while an interference cancellation based MUD has been proposed in [7], [8], [9]. The IC techniques can be broadly broken into serial and parallel schemes for canceling MAI.

In contrast to traditional computation systems which may be good at accurate and exact computation but have brittle operations, evolutionary computation provides a more robust and efficient approach for solving complex real world problem. Many evolutionary algorithms, such as Genetic algorithm (GA) [9], [11], [12], ant colony optimization (ACO) [13], simulated annealing (SA) [9], [15] , Short Term Taub Search (STTS)[9], Reactive Taub Search (RTS)[9] and particle swarm optimization (PSO) [9], [15], [16], [18], [19], [20], have been proposed.

In this paper, we consider the multiuser detection from a combinatorial optimization viewpoint. We present a novel approach to solve the problem of MUD in MC-CDMA systems in this paper. The initial population is created using the minimum-mean square error (MMSE) receiver, then PSO algorithm is applied so as the best individual can be selected based on likelihood function. PSO has some attractive characteristics. It has memory, so knowledge of good solutions is retained by all particles; whereas in GA, previous knowledge of the problem is destroyed once the populations changed. It has constructive cooperation between particles, particles in the swarm share information between them.

The rest of the paper is organized as follows. In section II, the MC-CDMA uplink model is described. The proposed PSO algorithm and PSO based MUD is presented in section III, section IV shows the computer simulation results and finally section V summarizes the paper.

II. RECEIVED SIGNAL MODEL

In the MC-CDMA system, the available frequency spectrum is split into a number of smaller frequency bands. Each band is used to transmit a narrowband direct sequence waveform. A K-user MC-CDMA system with BPSK modulation is considered. As a frequency selective Rayleigh fading channel, we assume a wide-sense stationary uncorrelated scattering (WSSUS) channel [22]. The received signal at the base station can be expressed as

$$r(t) = \sum_{l=\infty}^{\infty}\sum_{k=1}^{K}\sum_{p=-1s}^{P-1} b_{k,p}(l)\sum_{n=0}^{N-1} G_{k,Pn+p}(l)\, a_{k,n}\, \mathrm{Cos}\left[\omega_m\left(t - \tau_{k,Pn+p}\right) + \phi_{k,Pn+p}(l)\right] \times p_{T_b}(t - lT_b) + n(t) \quad (1)$$

Where, K is number of MC-CDMA users sending P parallel data symbols with binary data signal, and $a_{k,n} \in \{-1, +1\}$ is the n^{th} chip of the k^{th} user spreading codes with $p_{T_b}(t)$ is a rectangular pulse with amplitude 1 and bit duration T_b. Where $\omega_m = \omega_c + 2\pi(P_{n+p})\,\Delta f$ is the n^{th} subcarrier frequency of the p^{th} symbol, where ω_c is the common carrier frequency and $\Delta f = 1/T_b$ is the minimum carrier separation between subcarriers, τ_k is the time delay of the k^{th} user and $\in [0,T_b)$. For implicitly and without loss of generality, we suppose that the users are numbered such that $0 \le \tau_1 \le \tau_2 \le \cdots \le \tau_k = 0$. $G_{k,Pn+p}(l)$ is the complex gain of the received signal at the $(P_{n+p})^{th}$ subcarrier in the i^{th} data bit for the p^{th} symbol of k^{th} user and $\phi_{k,Pn+p}(l)$ is the received signal phase at the $(P_{n+p})^{th}$ subcarrier in the l^{th} data bit for the p^{th} symbol of k^{th} user. n(t) is an AWGN process with zero mean and two-sided PSD N0/2.

After the discrete Fourier transform (DFT) operation, the received signal for the $(P_{n+p})^{th}$ subcarrier during the l^{th} data interval at the base station can be expressed as

$$r_{Pn+p}(l) = \sum_{k=1}^{K} G_{k,Pn+p}(l)\, b_{k,p}(l)\, a_{k,n} + n(l), \quad (2)$$

Where $b_{k,p}(l) \in \{-1, +1\}$ is the p^{th} symbol of the k^{th} user during the l^{th} data duration. With the matrix form, we obtain the received signal during the ith data interval as

$$\mathbf{r} = \mathbf{Gba} + \mathbf{n} \quad (3)$$

Where

$$\mathbf{r} = [r_p\ r_{P+p} \cdots r_{P(N-1)+p}] \quad (4)$$

$$\mathbf{b} = \mathrm{diag}\,[b_{1,p}\ \ b_{2,p}\ \cdots\ b_{K,p}] \quad (5)$$

$$\mathbf{G} = \begin{bmatrix} G_{1,p} & G_{2,p} & \cdots & G_{K,p} \\ G_{1,P+p} & G_{2,P+p} & & G_{K,P+p} \\ \vdots & & \ddots & \vdots \\ G_{1,P(N-1)+p} & G_{2,P(N-1)+p} & \cdots & G_{K,P(N-1)+p} \end{bmatrix} \quad (6)$$

$$\mathbf{a} = \begin{bmatrix} a_{1,0} & a_{1,1} & \cdots & a_{1,N-1} \\ a_{2,0} & a_{2,1} & & a_{2,N-1} \\ \vdots & & \ddots & \vdots \\ a_{K,0} & a_{K,0} & \cdots & a_{K,N-1} \end{bmatrix} \quad (7)$$

$$\mathbf{n} = [n_p\ \ n_{P+p}\ \cdots\ n_{P(N-1)+p}] \quad (8)$$

A. MRC

The decision statistic for the p^{th} symbol of the l^{th} data duration of the users for conventional MRC receivers is thus obtained as

$$\mathbf{Z}_p(l) = \Re[\mathbf{G}^H.\mathrm{diag}(r).\mathbf{a}^T] \quad (9)$$

The decision statistic for the p^{th} symbol of the l^{th} data duration of the users for conventional MRC receivers is thus obtained as

$$\hat{\mathbf{b}}_p(l) = \mathrm{sign}[\mathbf{Z}_P(l)] \quad (10)$$

Where $[\ ]^H$ and $[\ ]^T$ are the Hermitian and transposition operation, respectively.

B. MMSE Detector

The LMMSE detector chooses the matrix $A = (R + \sigma^2\varepsilon^{-1})$, where ε is the identity matrix of order K (i.e. assuming all users transmit with equal power) and $R = G^H G$ and multiply A^{-1} to $\mathbf{Z}$ from (9), the result is

$$\mathrm{LMMSE} = \mathrm{sign}\,[A^{-1}\mathbf{Z}] \quad (11)$$

It reduces MAI and simultaneously minimizes noise enhancement caused by the decorrelator operation.

III. Improved Particle Swarm Optimization

PSO is a swarm intelligence method for global optimization modeled after the social behavior of bird flocking and fish schooling [15], [19]. Similar to other evolutionary algorithms such as GA, PSO conducts solution searching using a population of individual particles. It is based on the population of particles that fly in the solution space with velocity that is dynamically adjusted based on its own flying experience and that of the best among the swarm. The PSO principle is the movement of a group of particles, each one with its own position and velocity.

A. Elements of PSO

Each particle represents a candidate solution to the optimization problem. Each particle keeps track of the position of its individual best solution ($\mathbf{p}_{\text{best}}$) and the overall global best solution ($\mathbf{g}_{\text{best}}$) among $\boldsymbol{p}_{best}$ of all the particles in the population achieved so far, respectively, and both are stored to generate the new velocity of particle. By combining the cognition model and social model, the particle is accelerated toward $\mathbf{p}_{\text{best}}$ and $\mathbf{g}_{\text{best}}$ over the iterations. The cognition model represents private thinking from its own previous experience/memory of the particle itself toward $\mathbf{p}_{\text{best}}$. On the other hand, the social model represents collaboration of all the particles toward $\mathbf{g}_{\text{best}}$, according to the belief of the best experience of the population.

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. New velocity and position of the algorithm is updated by following equations

$$\mathbf{v}_d^i = w^i * \mathbf{v}_d^{i-1} + c_1 * \mathbf{r}_1 * (\mathbf{p}_{\text{best}}{}_d^{i-1} - \mathbf{x}_d^{i-1}) + c_2 * \mathbf{r}_2 * (\mathbf{g}_{\text{best}}{}_d^{i-1} - \mathbf{x}_d^{i-1}) \quad (12)$$

$$\mathbf{x}_d^i = \mathbf{x}_d^{i-1} + \mathbf{v}_d^i \quad (13)$$

Where, velocity of the particle $\mathbf{v}_d^i = [v_{1d}^i, v_{2d}^i, \dots, v_{Kd}^i]$ is a K-dimensional real-valued vector, and v_{kd}^i is the velocity of the data bit of the k^{th} (k = 1,2,…,K) active user of the d^{th} particle at i^{th} iteration. Similarly, position of the particle $\mathbf{x}_d^i = [x_{1d}^i, x_{2d}^i, \dots, x_{Kd}^i]$ is a candidate solution represented by a K-dimensional real-valued vector, where $\mathbf{x}_{kd}^i$ is the position of the data bit of the active user of the d^{th} particle at i^{th} iteration. Where $\mathbf{r}_1$ and $\mathbf{r}_2$ are two random parameters witch are chosen uniformly within the interval [0, 1]. This equation reveals that the new velocity is related to the old velocity weighted by w^i, and is also associated with the position of the particle itself and of the global best one by acceleration constants c_1 and c_2 respectively. Inertia weight factor is used to control the impact of the velocity of previous iterations on the velocity of current iteration. It tries to balance the global and local exploration abilities of the particle [17]. The acceleration constants represent the weighting of the stochastic acceleration terms to pull the particle toward $\mathbf{p}_{best}$ and $\mathbf{g}_{best}$ [17]. Low values of c_1 and c_2 allow particles to roam far from target regions before being tugged back, whereas high values result in abrupt movement toward or past the target region.

The system aims at finding the $\mathbf{x}_d^i$ with the minimum cost. Consequently, the objective function of a swarm for $\mathbf{x}_d^i$ for bit l is defined as

$$F(\mathbf{x}_d^i) = \sum_{n=0}^{N-1}\left[r_{Pn+p}(l) - \sum_{k=1}^{K} x_{kd}^i\, G_{k,Pn+p}(l)a_{k,n}\right]^2 \quad (14)$$

For each particle, compare its current objective value with the object value of its $\mathbf{p}_{best}$. If current value is better, then update $\mathbf{p}_{best}$ and its object value with the current position and objective value. Furthermore, determine the best particle of current swarm with the best objective values. If the objective value is better than the object value of $\mathbf{g}_{best}$, then update $\mathbf{g}_{best}$ and its objective value with the position and objective value of the current best particle.

B. PSO Algorithm

The steps of PSO-based multi-user detector for a K-user synchronous MC-CDMA system are shown in Fig. 1 and can be described as follows:

Step 1) Run the MRC/LMMSE detector.

Step 2) Initialization: A bad initial guess for the PSO-based MUD can result in poor performance because the BER could be saturated before convergence. As such, a good initial guess (e.g., MRC/MMSE detector output) is needed for initialization to obtain superior performance for the evolutionary computation technique.

Set the current iteration counter i=0. The result of the MRC/MMSE detector is set as the initial position of the first particle $\mathbf{x}_1^0$. For the initial position of d[th] particle (d=2, . . . , N_P), the sine of (d-1)[th] bit obtained from MRC/MMSE is reversed, i.e. for example initial position of second particle is $\mathbf{x}_2^0$ = [$-b_{1,p}$, $b_{2,p}$, · · ·, $b_{K,p}$]. So, the population size N_P becomes (K+1). Set $\mathbf{p}_{best}{}_d^0 = \mathbf{x}_d^0$ and evaluate $F(\mathbf{p}_{best}{}_d^0)$. $\mathbf{p}_{best}{}_{max}^0$ is denoted as the individual best particle position that minimizes the objective function F at iteration i=0 such that $F(\mathbf{p}_{best}{}_{min}^0) \leq F(\mathbf{p}_{best}{}_d^0)$ for d=1,2, . . . , N_P. Then, set $\mathbf{g}_{best}{}_d^0 = \mathbf{p}_{best}{}_{min}^0$. The initial velocity $\mathbf{v}_d^0$ is randomly chosen between [$-\mathbf{v}_d^{max}$, $\mathbf{v}_d^{max}$].

Step 3) Increase iteration counter and inertia weight factor: increase the iteration counter i = i +1 and update inertia weight w^i.

For the initial stage of the search process, large inertia weight is recommended to enhance the global exploration, whereas for the late stage, the inertia weight is reduced for better local exploration. The decrement function for decreasing

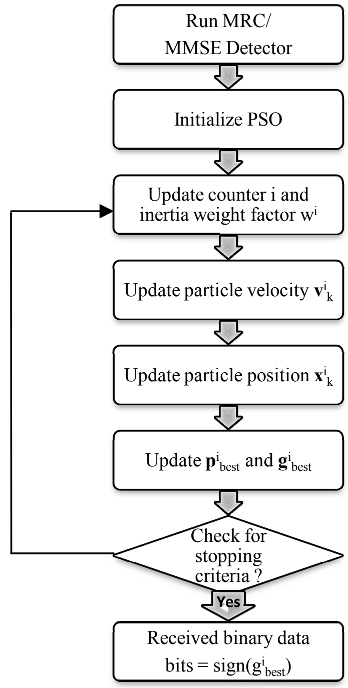

Fig. 1. Flow chart of MRC/MMSE PSO Algorithm

the inertia weight is given as $w^i = \alpha\, w^{i-1}$ [17], where α is the decrement constant, which is smaller than 1. In [22] various combinations of α and w have been studied. It is shown that promising performance can be achieved when w and α are close to 1.

Step 4) Update particle velocity $\mathbf{v}_d^i$: The velocity of the moving particles represented by a K-dimensional real-valued vector is calculated as given by (12).

The first term is the influence of the previous velocity to the current velocity. The second term is the cognition part, and the third term is the social part. Thus, (12) calculates the particle's current velocity according to its previous velocity, the distance of its current particle position from its own individual best particle position among $\mathbf{p}_{best}$, and the global best particle position $\mathbf{g}_{best}$.

Maximum velocity $\mathbf{v}^{max}$: The particle velocity is limited by the maximum velocity $\mathbf{v}_d^{max}$ = [$\mathbf{v}_{1d}^{max}$, $\mathbf{v}_{2d}^{max}$, . . . , $\mathbf{v}_{Kd}^{max}$], where $\mathbf{v}_d^{max}$ is the maximum velocity of the k[th] active user. $\mathbf{v}^{max}$ determines the resolution or fineness of the search. With the use of inertia weight, $\mathbf{v}^{max}$ can be set to be the value of the dynamic range of the variable. In our case, $\mathbf{v}^{max}$ can be set to 2 because the received bit should be equal to -1 or 1.

Step 5) Update particle position $\mathbf{x}_d^i$: the position of the particle is updated by (13)

Step 6) Update $\mathbf{p}_{best}{}_d^i$ and $\mathbf{g}_{best}{}_d^i$: Evaluate the objective values of all particles according to (14). Update the individual best and global best position of the particles only if the new values gives better value of objective function, i.e. the individual best position of the d[th] particle at the i[th] iteration is denoted as $\mathbf{p}_{best}{}_d^i$, which is determined by $F(\mathbf{p}_{best}{}_d^i) \leq F(\mathbf{x}_d^j)$ for all j ≤ i and global best ($\mathbf{g}_{best}{}_d^i$) particle position among all the individual best particle positions $\mathbf{p}_{\text{best}_d}^{i}$ at the i[th] iteration such that $F(\mathbf{g}_{\text{best}_d}^{i}) \le F(\mathbf{p}_{\text{best}_d}^{i})$ for d = 1, 2, . . . , N_P.

Step 7) Termination criteria: If a predefined stopping criterion is met, then output $\mathbf{g}_{\text{best}_d}$ and its objective value; otherwise go back to Step 3.

Step 8) Binary received data bit, $\hat{\mathbf{b}}_p$= sign ($\mathbf{g}_{\text{best}_d}^{i}$): The PSO algorithm was originally developed for the continuous optimization problem in real-valued space [20]. On the other hand, MUD belongs to combinatorial optimization problem in discrete binary space. One challenge of PSO-based MUD is to detect and output the received data bit in binary format. A discrete binary version of the PSO algorithm was developed in [20], where the particle is represented by a binary variable, and the polarity of each bit might be flipped by comparing a random number against a threshold probability determined by sigmoid function. In this paper, we introduce a simple alternative approach to address this issue. The parameters $\mathbf{x}_d^i$, $\mathbf{v}_d^i$, $\mathbf{p}_{\text{best}_d}^{i}$ and $\mathbf{g}_{\text{best}_d}^{i}$ are still treated as a real-valued variable during the run of the optimization. After termination of optimization, the binary received data bit is set equal to sign($\mathbf{g}_{\text{best}}t$). Thus, the binary received data bit = 1 if $\mathbf{g}_{\text{best}} \ge 0$; otherwise, the binary received data bit = −1. Our approach can avoid the generation of random number and sigmoid function to determine the polarity flipping for each bit of each particle at each iteration. Hence, the MRC-PSO/MMSE-PSO MUD can reduce the computation, as compared with MRC-PSO MUD in [10]

C. Computational Complexity

The computational complexity/bit of the optimum detector grows exponentially with the number of active users K on the order of $O(2^K)$ [21]. The computational complexity/bit of MMSE detector is linear with K on the order of O(K). With the number of the particle population N_P and the maximum number of iterationsN_I, the computational complexity/bit of our PSO-based MUD is $O(N_P N_I)$. Both $O(N_P)$ and $O(N_I)$ can be inferred to have a linear relationship with the dimensionality of the problem of the number of active users K. Hence, on the whole, the order of computational complexity/bit of the MRC-PSO and MMSE-PSO MUD is $O(K^2)$, which is the same as that of GA MUD in [12]. Although the orders of complexity of the MRC-PSO and MMSE-PSO MUD are higher than that of the MRC/MMSE detector, it is still worthwhile to incorporate PSO-based MUD considering the BER improvement to be presented in the simulation results of Section IV. However in our proposed scheme larger value of K doesn't require larger value of N_P and N_I. Where as in [10] requires more complex search space for higher values of K.

IV. Simulation Results

In this section, we present simulations to evaluate the BER performance of the MRC-PSO and MMSE-PSO MUD. We have described the iterative and diversity techniques for uplink MC-CDMA mobile systems. Computer simulations have been carried out for an MC-CDMA system with 64 sub-carriers, each using BPSK. To focus on the BER

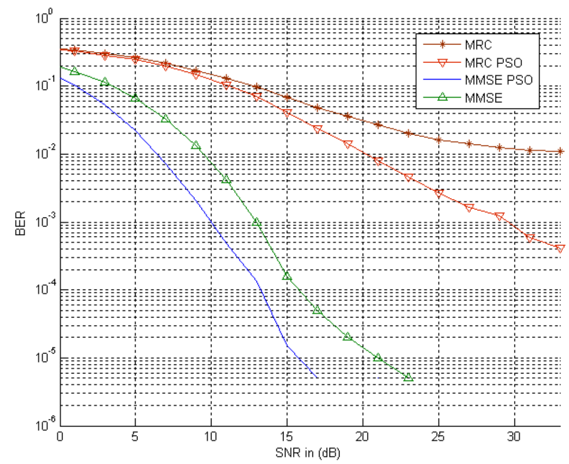

Fig. 2. Comparison of average BER versus signal-to-noise ratio for c_1, c_2 = 2 and K=25 for PSO based MUD in MC-CDMA system.

variations on the different partial cancellations, this investigation assumes that perfect subcarrier synchronization has no frequency offset and no nonlinear distortion for the MC-CDMA system. Therefore, we assume a quasi-synchronous uplink channel, and then discuss the BER performance of MC-CDMA systems with Walsh codes over frequency-selective fading channels in this study. The following parameters are empirically selected for the optimizations, and have used a swarm of K particles.

The acceleration constant c_1 and c_2 are set to 2 by [22], on average; it can make the search cover all the surrounding regions centered at the individual best particle position $\mathbf{p}_{\text{best}}$ and the global best particle position $\mathbf{g}_{\text{best}}$ [22]. We choose the initial inertia weight $w^0 = 1$ and the decrement constant α = 0.99, respectively. The maximum number of iterations of the PSO algorithm N_I is 50, which means that the PSO will stop if the number of iterations = 50. $\mathbf{v}^{max}$ and $\mathbf{v}^{min}$ is taken as 2 and -2 respectively.

Fig. 2 plots the BER performance of our proposed PSO algorithm along with MRC and MMSE, i.e., MRC-PSO and MMSE-PSO detectors against the bit signal-to-noise ratio (SNR), given the number of active user K = 24 for the synchronous MC-CDMA system. For the purpose of comparison, the BERs of MRC, MRC-PSO, MMSE, and MMSE-PSO are taken. It is shown that the simple MRC has a poor performance when the numbers of active users K are reasonably large. The MRC-PSO and MMSE-PSO MUD achieve a better BER performance, as compared with the MRC and MMSE Detectors.

V. Conclusion

In this paper, we proposed a new evolutionary algorithm of PSO-based multistage multi-user detector to improve the performance of MC-CDMA system. The output of the MRC/MMSE detector is used as the first stage to initialize the position of a particle. Then, the modified PSO algorithm optimizes the objective function incorporating the linear system of the MRC/MMSE detector to detect the received data bit. The final received binary data bit is obtained by a simple sign function to discretize the real-valued result of the PSO algorithm. We have shown that the BER performance of the MRC-PSO and MMSE-PSO detectors are improved compared to the MRC and MMSE detectors.

Our proposed scheme performs better even on increasing the number of users. Our study highlights the feasibility of PSO as a powerful solution for the MUD problem for MC-CDMA system with a significant number of active users in the system.

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