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A Mutated Ant Colony Optimization Algorithm for Multiuser Detection

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Abstract: Multiuser detection, which can efficiently mitigate the multiple access interference, is a hot topic nowadays for CDMA systems. In this research, a mutated ant colony optimization (MACO) algorithm is proposed by introducing the mutation mechanism to the ACO algorithm and is applied to multiuser detection. Compared with the ACO multiuser detector, the presented MACO multiuser detector can lead to quicker convergence and avoid local optima with almost the same computational complexity. Via computer simulations in CDMA communication system, it is shown that the performance of MACO multiuser detector in reducing the near-far effect and bit-error rate is much better than that of ACO multiuser detector and is also close to or even equal to the performance of optimal multiuser detector.

Key words: Code Division Multiple Access (CDMA), ant colony optimization (ACO), multiuser detection, mutated evolutionary algorithm

INTRODUCTION

In wireless Code Division Multiple Access (CDMA) systems, multiple access interference (MAI) is the main source of the performance degradation. The MAI is caused by other users in the channel and makes the conventional detector (CD) no longer reliable. Multiuser detection can efficiently mitigate the MAI and has been a subject of intense research in recent years (Xu *et al.*, 2006). Verdu first proposed the optimal multiuser detector (OMD) and it is shown to be near-far resistant and has the optimal performance, however, the exponential complexity in the number of users makes it impractical to use in current CDMA systems (Verdu, 1986). Therefore, research efforts have been concentrated on the development of suboptimal detectors, which exhibit good near-far effect resistant properties, have low computational complexity and achieve relatively high performance, such as MMSE detector (Kohli and Mehra, 2007), Hopfield neural network detector (Liu *et al.*, 2006), adaptive least mean square filter based detector (Sivakumar *et al.*, 2006) and stochastic cellular neural network detector (Wu *et al.*, 2007).

Ant colony optimization (ACO) algorithms take inspiration from the foraging behavior of some ant species. These ants deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony (Dorigo *et al.*, 2006). ACO algorithms have already successfully been used in solving discrete optimization (Aguilar *et al.*, 2004) and

they can also be used in multiuser detection as a kind of suboptimal detector (Lain and Lai, 2007). However, for the positive feedback rule of the pheromone accumulation, we may not get a global optimum because it stops searching early. To overcome the disadvantages of conventional ACO algorithm, many improved ACO algorithms have been proposed, especially the ones hybrid with artificial intelligence algorithms, such as genetic algorithm and immune algorithm (Lee *et al.*, 2008; Qin *et al.*, 2006). Though these algorithms can achieve much better performance, the computational complexity of them increases greatly and they are no longer suitable to be applied to the fields with high real-time requirement like multiuser detection.

In this study, a mutated ant colony optimization (MACO) study is proposed to solve the multiuser detection problem. The algorithm is formed by only introducing the mutation operation of Genetic Algorithm (GA) to the ACO algorithm (Koehler, 1997), because the problems to be solved are not very complex and the real-time requirement is strict in multiuser detection. By doing so, the presented MACO multiuser detector enhances the local searching performance, expands the diversity of solutions, avoids local optima and converges quicker. The efficiency of algorithm is verified via computer simulations in CDMA communication system and it is shown that the performance of MACO multiuser detector in reducing the near-far effect and bit-error rate is much better than that of ACO multiuser detector and is also close to or even equal to the performance of optimal multiuser detector.

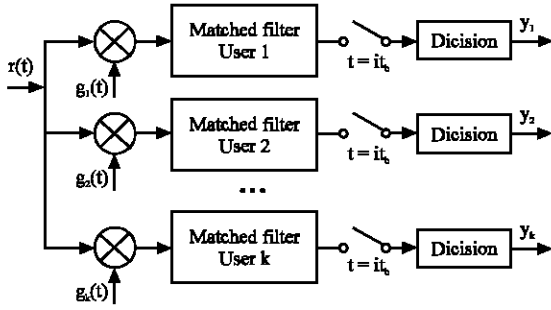


Fig. 1: The conventional detector

TRADITIONAL MULTIUSER DETECTION METHODS

Conventional detector: Assuming there are K users of a CDMA system in a synchronous single-path channel, the received signal can be expressed as:

$$r(t) = \sum_{k=1}^K A_k(t)g_k(t)d_k(t) + n(t), \quad (1)$$

where, $A_k(t)$, $g_k(t)$ and $d_k(t)$ are the amplitude, signature code waveform and information of the k th user, respectively. $n(t)$ is additive white Gaussian noise (AWGN), with a two-sided power spectral density of $N_0/2$ W/Hz.

The CD is composed of a bank of K matched filters and can be shown in Fig. 1.

In Fig.1, the existence of MAI has a significant impact on the capacity and performance of the CD system because the CD follows a single-user detector strategy. As the number of interfering users increases, the amount of MAI increases.

Optimal multiuser detector: Verdu has shown that the OMD may be achieved by producing an estimate for the information vector transmitted based on the maximization of the logarithm of the likelihood function. The objective function of the OMD is given as:

$$b_{opt} = \arg \max \{ 2Y^T Ab - b^T Hb \}, \quad (2)$$

where, $b \in \{+1, -1\}$, $Y^T = (y_1, \dots, y_K)$ is the row vector consisting of the sampled outputs of the matched filters, A is the diagonal matrix consisting of the corresponding received amplitudes and $H = A^T R A$, in which R is a $K \times K$ uniform correlation matrix.

Despite the huge performance and capacity gains over the CD, the OMD is not practical. The exponential complexity in the number of users makes the cost of this

detector too high. Consequently, research efforts have been concentrated on the development of suboptimal multiuser detectors that exhibit good near-far resistance, reasonable implementation complexity and comparable BER performance to that of the OMD.

ACO MULTIUSER DETECTOR

Ant colony optimization: ACO was firstly used to solve traveling salesman problem (TSP), so we use the TSP as a concrete example to illustrate the basic model of ACO.

The main characteristic of ACO is that, after each iteration, the pheromone values are updated by all the M ants that have built solutions. The pheromone τ_{ij} , associated with the edge joining cities i and j , is updated as follows:

$$\tau_{ij} \rightarrow (1-\rho) \times \tau_{ij} + \sum_{m=1}^M \Delta \tau_{ij}^m, \quad (3)$$

where, ρ is the evaporation rate, M is the number of ants and $\Delta \tau_{ij}^m$ is the quantity of pheromone laid on edge (i, j) by ant m .

In the construction of a solution, ants select the following city to be visited through a stochastic mechanism. When ant m is in city i and has so far constructed the partial solution s^p , the probability of going to city j is given by:

$$p_{ij}^m = \begin{cases} \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{c_l \in N(s^p)} [\tau_{il}]^\alpha [\eta_{il}]^\beta} & \text{if } c_j \in N(s^p), \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

where, $N(s^p)$ is the set of feasible components; that is, edges (i, l) where l is a city not yet visited by the ant m . The parameters α and β control the relative importance of the pheromone versus the heuristic information η_{ij} , which is given by:

$$\eta_{ij} = \frac{1}{d_{ij}}, \quad (5)$$

where, d_{ij} is the distance between cities i and j .

ACO multiuser detector: As the speciality of multiuser detection in the CDMA system, the ACO algorithms should be adjusted if we want to apply them to the multiuser detection. The adjustments are as follows.

For the K users in the systems are independent, without losing generality, we can let each ant travel in the fixed order from the 1st user to the Kth user. In this case, the ants should not decide whether the user has been traveled.

As there is not any heuristic information, we can discard parameters η_{ij} , α and β . Because the transmitted information by each user can only be +1 or -1, the probability of what value the k th user transmitted decided by the ant m at the time t is given by:

$$p_{kj}^m(t) = \frac{\tau_{kj}(t)}{\sum_{j \in \{-1,+1\}} \tau_{kj}(t)}, \quad k=1,2,\dots,K, \quad j=+1 \text{ or } -1. \quad (6)$$

The decision of which is the best solution is based on the values of the objective function in Eq. 2 and the solution that has the largest value is the best.

Because the datum in multiuser detection should be processed in real time, only the best ant in the current iteration deposits the pheromone after each iteration, but the pheromone on all the paths still evaporates.

Through the rules set above, multiuser detection can be described as a path-choosing problem which can be solved by ACO algorithms.

MACO MULTIUSER DETECTOR

Mutation mechanism: Genetic Algorithm (GA) is a powerful tool to solve combinatorial optimizing problems and it is first proposed by John Holland professor in 1975. It solves the formulated optimization problem by using the idea of Darwinian evolution. Basic evolution operations, including crossover, mutation and selection, make GA be apt to perform global search very effectively. In the multiuser detection, the problems to be solved are not very complex and the real-time requirement is strict, so only the mutation operation is introduced to the ACO algorithm and a MACO algorithm is proposed for multiuser detection.

In the MACO multiuser detector, assuming that the local best solution after the n th iteration is $b_{nbest}=(b_{1nbest}, \dots, b_{Knbest})^T$. Randomly choose one or more bits in the b_{nbest} , handle them with logical not operator and keep the other bits unchanged. Through this mutation operation, the mutated solution b_{nbest}' of b_{nbest} can be got. If b_{nbest}' is better than b_{nbest} , replace b_{nbest} by b_{nbest}' . Otherwise the local best solution remained unchanged.

The number of the mutated bits is decided by the number of users in the system K and the larger K is, the more bits are mutated. If K is extremely large, the number of mutated bits can be set to decrease as iterations carried on.

Through introducing the mutation mechanism to ACO multiuser detection, the local searching performance is enhanced, the diversity of solutions is expanded and early convergence can be avoided.

MACO multiuser detector: MACO is applied to multiuser detection following the rules described above and the MACO multiuser detector can be got. It is represented by the following steps:

- Step 1: Initialize of parameters, including the number of iterations N_c , the population of the ant colony M , the evaporation rate ρ and the initial value of the pheromone $\tau(0)$.
- Step 2: Set the outputs of the matched filters in Fig. 1 as the initial global best solution.
- Step 3: M ants travel from the 1st user to the K th user following Eq. 6 and then we can get M solutions in the n th iteration.
- Step 4: Compare the M solutions based on the Eq. 2 and set the solution that has the largest value (equal to C_n) of Eq. 2 as the local best solution b_{nbest} in this iteration.
- Step 5: Calculate the mutated solution b_{nbest}' of b_{nbest} following the mutation mechanism described above and get the value of the Eq. 2 C_n' using b_{nbest}' . Compare C_n and C_n' . If C_n' is larger than C_n , replace b_{nbest} by b_{nbest}' and replace C_n by C_n' .
- Step 6: Update the pheromone as follows:

$$\tau_{kj}(t+1)=(1-\rho)\times\tau_{kj}(t)+\Delta\tau_{kj}, \quad k=1,2,\dots,K, \quad j=+1 \text{ or } -1, \quad (7)$$

$$\Delta\tau_{kj} = \begin{cases} (C_n+Q)/r & (k,j) \in b_{nbest}, \\ 0 & \text{otherwise,} \end{cases} \quad (8)$$

where, $\Delta\tau_{kj}$ is the quantity of pheromone laid on edge (k, j) of the k th user with the value J , Q is a positive constant to ensure $(C_n+Q)=0$ and R is a constant to adjust the value of $\Delta\tau_{kj}$.

- Step 7: Compare the local best solution with the global best solution. If the local best solution is better than the global best solution, set the local best solution as the global best solution.
- Step 8: Output the global best solution if stopping criterion is satisfied, or return to Step 3.

Computational complexity: The computational complexity of an algorithm can be measured by the number of multiplications and additions. The computational complexity CD, ACO multiuser detector, MACO multiuser detector and OMD is compared in Table 1 when there are K users in the system and each detects only one bit data.

In Table 1, N is the length of PN sequences, M is the number of the ants in the colony, N_c is the number of iterations. In this Study, they are set as $K = 10$, $M = 15$

Table 1: Computational complexity comparison

Detector	Computational complexity
CD	$2KN$
ACO multiuser detector	$[2K(K+N)+5K+1]MN_c$
MACO multiuser detector	$[2K(K+N)+5K+1]MN_c$
OMD	$[2K(K+N)+5K+1]2^K$

and $N_c = 20$, so the computational complexity of ACO multiuser detector and MACO multiuser detector is the same and 80.5% lower relative to OMD and it will be much less than that of OMD when K is even larger.

RESULTS AND DISCUSSION

In order to evaluate the performance of the MACO multiuser detector, a DS-CDMA system using it is designed as Fig. 2.

In Fig. 2, the number of users $K=10$ in the CDMA system and the length of PN sequences used is 15. The number of the ants $M=K=10$, the number of iterations $N_c = 20$, the evaporation rate $\rho = 0.3$, the parameters Q and R in Eq. 8 are equal to 200 and 15 and there is only one bit of information transmitted mutated in each iteration. The received signal $r(t)$ is handled in the matched filter bank, the outputs of which are fed into the MACO multiuser detector and then we can get the estimate of the baseband information transmitted of each user. A variety of simulation experiments are presented comparing the performance of the CD, the ACO multiuser detector, the MACO multiuser detector and the OMD in the system depicted in Fig. 2.

First, the near-far effect resistant performance of these detectors is compared. In order to illustrate explicitly, only the transmitted energy of the first user E_1 changes and the energy of other users E_k ($k=2, 3, \dots, K$) is all unchanged with their signal-noise ratios (SNR)=6dB.

From the simulation results in Fig. 3, we can see that near-far effect resistant performance of the MACO multiuser detector is much better than the CD and the ACO multiuser detector and is close to OMD, especially when the near-far effect is serious.

Second, the performance of these detectors with no near-far effect is compared. In this case, the transmitted energy of all the users is ensured to be equal ($E_1 = E_k$, $k = 2, 3, \dots, K$) and unchanged.

It is shown in Fig. 4 that if the near-far effect is not considered, the BER of the MACO multiuser detector is much lower than that of the CD and the ACO multiuser detector and is close to the BER of OMD.

Therefore, the simulation results show that the overall performance of the MACO multiuser detector is

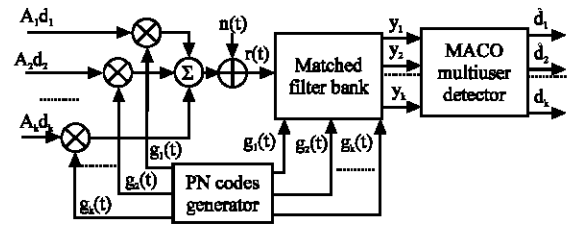


Fig. 2: The block diagram of a MACO multiuser detection system

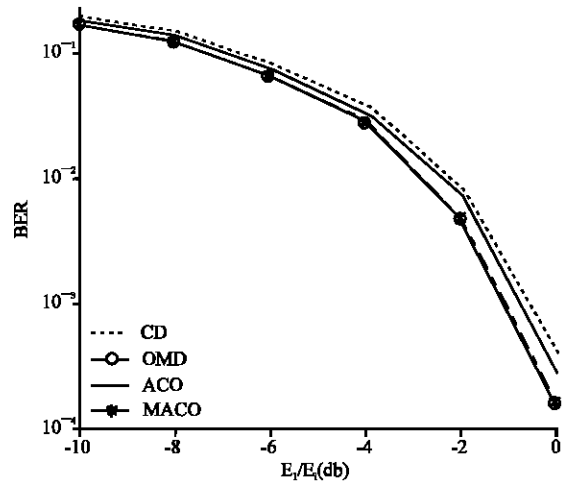


Fig. 3: Bit-error rate vs. near-far ratio

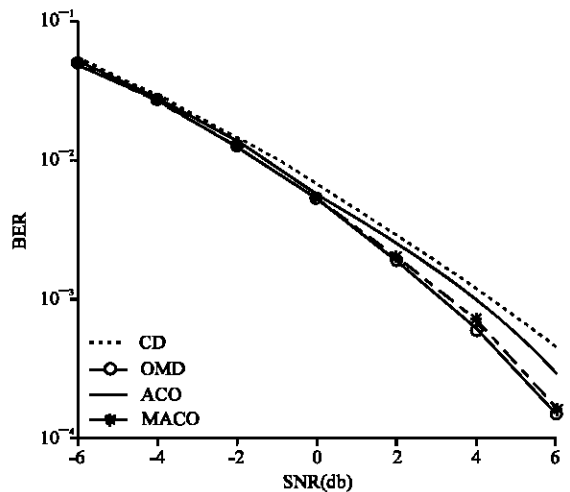


Fig. 4: Bit-error rate vs. signal-noise ratio

much better than the ACO multiuser detector and is close to or even equal to OMD by introducing the mutation mechanism to the ACO algorithm, so it is more suitable as a suboptimal multiuser detection scheme in CDMA systems.

CONCLUSION

The ACO algorithm is suitable for solving discrete optimization problems with excellent performance, however, for the positive feedback rule of the pheromone accumulation, it may stop searching early and usually only a local optimum can be got. In this study, a MACO algorithm is proposed by introducing the mutation mechanism to the ACO algorithm, so the local searching performance is enhanced. The MACO algorithm is then applied to multiuser detector and MACO multiuser detector is proposed. Through computer simulations, it is shown that the BER-reducing and near-far resistant performance of the MACO multiuser detector is superior to that of ACO multiuser detector and is close to or even equal to OMD.

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