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A hybrid ant colony optimization algorithm for optimal multiuser detection in DS-UWB system

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ABSTRACT

A hybrid ant colony optimization algorithm is proposed by introducing extremal optimization local-search algorithm to the ant colony optimization (ACO) algorithm, and is applied to multiuser detection in direct sequence ultra wideband (DS-UWB) communication system in this paper. ACO algorithms have already successfully been applied to combinatorial optimization; however, as the pheromone accumulates, we may not get a global optimum because it can get stuck in a local minimum resulting in a bad steady state. Extremal optimization (EO) is a recently developed local-search heuristic method and has been successfully applied to a wide variety of optimization problems. Hence in this paper, a hybrid ACO algorithm, named ACO–EO algorithm, is proposed by introducing EO to ACO to improve the local-search ability of the algorithm. The ACO–EO algorithm is applied to multiuser detection in DS-UWB communication system, and via computer simulations it is shown that the proposed hybrid ACO algorithm has much better performance than other ACO algorithms and even equal to the optimal multiuser detector.

1. Introduction

Swarm intelligence is a relatively new approach to solve the problems that takes inspiration from the social behaviors of insects or other animals. In particular, ants have inspired a number of methods and techniques among which the most successful one is the general purpose optimization technique known as ant colony optimization (ACO). ACO algorithms take inspiration from the foraging behavior of ant species (Goss, Aron, Deneubourg, & Pasteels, 1989). These ants deposit pheromone on the ground in order to mark the favorable paths that should be followed by other members of the colony. ACO exploits a similar mechanism for solving optimization problems (Dorigo, Birattari, & Stützle, 2006; Mullen, Monekosso, Barman, & Remagnino, 2009; Sim & Sun, 2003).

The first ACO algorithm, ant system (AS), is proposed as a means of solving the traveling salesman problem (TSP) (Dorigo, Maniezzo, & Colorni, 1996). AS has gained a great success in solving combinatorial optimization problems; however, its performance is still worse than some other metaheuristic algorithms (Laguna & Glover, 1993; Zhen-Ping & Bavarian, 1992). Therefore many other ACO algorithms are proposed inspired by AS, the performance of which is improved remarkably (Dorigo et al., 2006). The main ACO algorithms presented in the literatures are: ant-Q (Dorigo & Gambardella, 1996), ant colony system (ACS) (Dorigo & Gambardella, 1997), MAX–MIN ant system (MMAS) (Stützle & Hoos, 2000), rank-based ant system (Bullnheimer, Hartl, & Strauss, 1999), ANTS (Maniezzo, 1999), hyper-cube ant system (Blum & Dorigo, 2004), multi-objective ant colony system algorithm (MOACSA) (Yagmahan & Yenisey, 2010), population declining ant colony optimization (PDACO) (Wu, Zhao, Ren, & Quan, 2009), and mutated ant colony optimization (MACO) (Zhao, Wu, Zhao, & Quan, 2010). The development of bio-inspired methodologies based on ant colony inspired algorithm systems is an emergent research area with applications in areas such as robotics (Lerman, Galstyan, Matinolli, & Ijspeert, 2002), quadratic assignment problems (Colorni, Dorigo, & Maniezzo, 1991), TSP (Li & Gong, 2003), and feature subset selection (Sivagaminathan & Ramakrishnan, 2007).

Ultra-wideband (UWB) transmission has recently attracted much attention in both academia and industry for applications in wireless communications (Ghavami, Michael, & Kohno, 2004; Qiu, Liu, & Shen, 2005; Win & Scholtz, 2000). The UWB systems can perform very high transmission data rate, and they are mainly applied to the indoor transmission. The transmission data rate can get up to 100 Mbps at the transmission distance of 10 m, and it arises to 200 Mbps when the transmission distance is reduced to 4 m. In direct sequence UWB (DS-UWB) system, a large number

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of users can communicate simultaneously on the same frequency band; however, it also creates multiple access interference (MAI). The MAI makes the conventional detector (CD), which can demodulate only one spread-spectrum signal without considering other signals, unreliable and insensitive to near-far effect in a multiuser environment. For this reason multiuser detection, which can overcome this problem, is a hot topic now for DS-UWB systems (Kaligineedi & Bhargava, 2008). We can use the optimal multiuser detector based on the maximum likelihood (ML) rule proposed by Verdu (1986) for code division multiple access (CDMA) systems. In the DS-UWB systems, the optimal multiuser detection (OMD) based on ML rule was proposed by Yoon and Kohno (2002). OMD 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 DS-UWB system. 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 (Cheng, Wen, Hsu, & Huang, 2009; Lin & Wang, 2008). ACO algorithms can also be used in multiuser detection in CDMA system as a kind of suboptimal detectors, in which the length of the tour in TSP is related to the objective function of the OMD (Hijazi & Natarajan B., 2004; Zhao, Wu, Zhao, & Quan, in press). However, ACO algorithms have never been applied to the multiuser detection in DS-UWB system.

Recently, a general-purpose local-search heuristic algorithm, extremal optimization (EO) has been proposed (Boettcher & Percus, 1999; Boettcher & Percus, 2000). EO is based on the Bak–Sneppen (BS) model (Bak & Sneppen, 1993), which shows the emergence of self-organized criticality (SOC) (Bak, Tang, & Wiesenfeld, 1987) in ecosystems. The evolution in this model is driven by a process where the weakest species in the population, together with its nearest neighbors, is always forced to mutate. Large fluctuations ensue, which enable the search to effectively scaling barriers to explore local optima in distant neighborhoods of the configuration space.

To avoid premature convergence of ACO algorithm, a novel hybrid ACO algorithm, named ACO–EO is proposed by introducing EO to ACO to improve the local-search ability of ACO algorithm in this paper. In the algorithm, ACO ensures that the search converges faster, while EO makes the search to jump out of local optima due to its strong local-search ability. In this paper, ACO–EO multiuser detector is proposed by applying ACO–EO algorithm to multiuser detection. Via simulations, it is shown that the ACO–EO multiuser detector has a much better performance in reducing the near-far effect than the ACO multiuser detector, PDACO multiuser detector, and MACO multiuser detector, as well as a superior performance in bit-error rate (BER). The performance of ACO–EO multiuser detector is even equal to OMD.

The remainder of this paper is organized in four sections. In Section 2, some preliminaries about ACO are reviewed. In Section 3, EO algorithm is introduced and the hybrid ACO–EO algorithm is proposed. In Section 4, the background of multiuser detection in DS-UWB is reviewed, and ACO–EO multiuser detector for DS-UWB is proposed. In Section 5, the performance of the ACO–EO multiuser detector is compared with the ACO multiuser detector, PDACO multiuser detector, MACO multiuser detector, and some other detectors.

2. Ant colony optimization algorithms

Many ACO algorithms have been proposed. Here we present the original AS, and its two most successful variants: MMAS and ACS. In order to illustrate the differences between these algorithms, we use the TSP as a concrete example.

2.1. Ant system

AS is the first proposed ACO algorithm. Its main characteristic 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:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij} + \sum_{m=1}^{M} \Delta\tau_{ij}^{m}, \tag{1}$$

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:

$$\Delta\tau_{ij}^{m} = \begin{cases} Q/L_m & \text{if ant } m \text{ used edge } (i,j) \text{ in its tour,} \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where Q is a constant, and L_m is the length of the tour constructed 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:

$$p_{ij}^{m} = \begin{cases} \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{c_{il}\in N(s^p)}[\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}} & \text{if } c_{ij} \in \mathrm{N}(s^p), \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

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 vs. the heuristic information η_{ij}, which is given by:

$$\eta_{ij} = \frac{1}{d_{ij}}, \tag{4}$$

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

AS has gain a great success in solving TSP, however, as the scale of TSP increases the performance of AS decreases seriously compared with other metaheuristic algorithms. So, most of the research on ACO has been focused on the methods to improve AS. The most successful ones are ACS and MMAS.

2.2. MAX–MIN ant system

MMAS is an improvement on the original AS. Its characterizing elements are that only the best ant updates the pheromone trails and that the value of the pheromone is bounded. The pheromone update is implemented as follows:

$$\tau_{ij} \leftarrow \left[(1-\rho)\cdot\tau_{ij} + \Delta\tau_{ij}^{\text{best}}\right]_{\tau_{\min}}^{\tau_{\max}}, \tag{5}$$

where $\tau_{\max}$ and $\tau_{\min}$ are respectively the upper and lower bounds imposed on the pheromone; the operator $[x]_b^a$ is defined as:

$$[x]_b^a = \begin{cases} a & \text{if } x > a, \\ b & \text{if } x < b, \\ x & \text{otherwise,} \end{cases} \tag{6}$$

and $\Delta\tau_{ij}^{\text{best}}$ is:

$$\Delta\tau_{ij}^{\text{best}} = \begin{cases} 1/L_{\text{best}} & \text{if}(i,j) \text{ belongs to the best tour,} \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

where L_{best} is the length of the tour of the best ant. This may be either the best tour found in the current iteration (iteration-best, L_{ib}) or the best solution found since the start of the algorithm (best-so-far, L_{bs}) or a combination of both.