Neurocomputing 148 (2015) 46–53

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Pheromone mark ant colony optimization with a hybrid node-based pheromone update strategy

Xiangyang Deng [a,*], Limin Zhang [b], Hongwen Lin [a], Lan Luo [c]

[a] Department of Electric and Information Engineering, Naval Aeronautical and Astronautical University, 264001 Yantai, China
[b] Department of Scientific Research, Naval Aeronautical and Astronautical University, 264001 Yantai, China
[c] Basic Teaching Department, Yantai Vocational College, 264001 Yantai, China

ARTICLE INFO

Article history:
Received 24 April 2012
Received in revised form
13 November 2012
Accepted 26 December 2012
Available online 1 August 2014

Keywords:
Ant colony optimization
Pheromone mark
Node-based pheromone
k-nearest-neighbor nodes
PM-ACO
Shortest path problem

ABSTRACT

An improved ant colony optimization (ACO) algorithm called pheromone mark ACO abbreviated PM-ACO is proposed for the non-ergodic optimal problems. PM-ACO associates the pheromone to nodes, and has a pheromone trace of scatter points which are referred to as pheromone marks. PM-ACO has a node-based pheromone update strategy, which includes two other rules except a best-so-far tour rule. One is called r-best-node update rule which updates the pheromones of the best-ranked nodes, which are selected by counting the nodes' passed ants in each iteration. The other one is called relevant-node depositing rule which updates the pheromones of the k-nearest-neighbor (KNN) nodes of a best-ranked node. Experimental results show that PM-ACO has a pheromone integration effect of some neighbor arcs on their central node, and it can result in instability. The improved PM-ACO has a good performance when applied in the shortest path problem.

1. Introduction

Ant Colony Optimization (ACO) [1] originating from the foraging behavior of the ant colony is a novel evolutionary algorithm. In reality, the ant individuals have simple behaviors when searching food, allocating tasks, cooperative transport, and so on. At the same time, the ant colonies show a emerged higher intelligence so that they can solve complex problems that in some cases far exceed the individual capabilities. ACO is firstly proposed by Dorigo et al. [2], and has some advantages such as highly parallelism, easy to be understood and implemented and so on. After that, some extensions as well as a number of changes were proposed by the scholars around the world. It has been successfully applied in many optimization problems. Hideki Katagiri introduced the incorporation of tabu search and ant colony optimization for solving k-minimum spanning tree problems (k-MST) [3]. To lower the power consumption in wireless sensor networks, Ho et al. [4] utilized the ladder diffusion phase to construct a route map, and then found a optimal path by ACO. Chen et al. [5] suggested a novel information exchange strategy ACO to get a optimal solution for each processor in a massively parallel processors condition. Sundareswaran and Srinivasarao Nayak [6] designed a feedback controller based on ant colony optimization to implement a closed induction motor starting system. Paplinski [7] proposed an Interpolated Ant Colony Optimization (IACO) for continuous domain optimization, and it was applied in linear dynamic systems identification.

Most of published papers concentrated on the hybridization of different algorithms, and there are seldom papers studying the generalized model of pheromone structure. Pheromone structure is a key module of the ACO, and the basic model of ACO solving problems is to build a path on a construction graph $G=(V,E)$ where the nodes set V corresponds to the elements of a solution for the considered problem and arcs set E corresponds to the connections of the elements [8]. It is droved by some artificial ants, which construct tours on the construction graph and deposit pheromones on the arcs, and eventually achieve the goal of getting an optimal path.

2. Pheromone trail and pheromone mark

When ants construct solutions along the arcs on the construction graph, the pheromone trace left by the ants can be classified into two types. One is built upon the continuous moving of ants, and its trails are formed by the traversed arcs with pheromones. The other is built upon the discrete moving of ants and it associates pheromones to the nodes. They are demonstrated in Fig. 1.

The two pheromone models were firstly discussed by Dorigo et al. [9]. The pheromone models were embedded into a hyper-

* Corresponding author.
E-mail addresses: xavior2012@yahoo.cn (X. Deng), iamzlm@163.com (L. Zhang).

http://dx.doi.org/10.1016/j.neucom.2012.12.084
0925-2312/

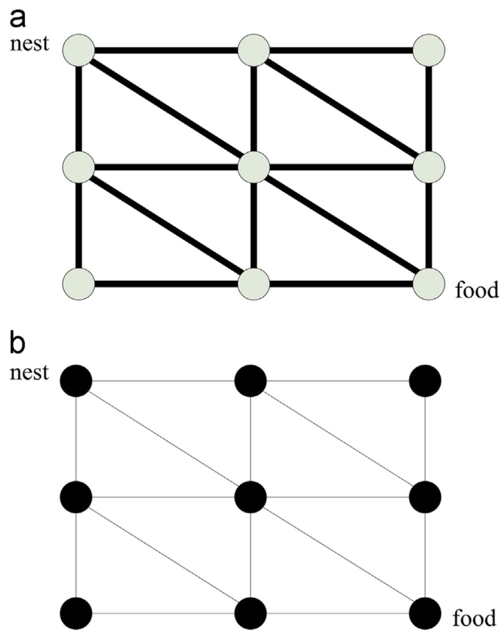

Fig. 1. Two types of pheromone model. The left picture demonstrates that the pheromone is associated with traversed bolded arcs, and the right one demonstrates that the pheromone is associated with traversed black nodes.

cube framework (HCF), which introduced the two mentioned pheromone traces called trail parameters in [9]. The trail parameters could be associated to nodes or arcs. In most of the ACO algorithms, the parameter associated to arcs, such as Ant System (AS) [10] and its successors, ACS [11] and its successors, and the ACO algorithms applied in various engineering fields [12,13]. This is derived directly from the ants' forging behaviors and can be easily understood. However, there are several situations where the parameter associated to nodes and they were used for algorithm designers to define the solution components. In [14], an ACO approach was proposed to solve the set covering problem (SCP), whose pheromone trails are associated with components, and represent the desirability that a component is selected to be involved in a solution. In [15], Michel et al. developed an ACO algorithm to solve the shortest common supersequence problem (SCSP), and they associated the pheromone to the elements denoted the characters in a string. Although the same pheromone trail sign τ_{ij} was used, the two subscripts just represented the positions of the character in a string. In [16], an improved ACO was proposed to solve the continuous optimization problem based on a grid model of continuous space, and it associated the pheromones to the discrete grid nodes. Chen [17] discussed a modified ACO algorithm which deposited pheromones on the nodes. The algorithm introduced a dynamic strategy of pheromone evaporation factor to enhance the algorithm's performance, and was applied in robot path planning problem.

In the above-mentioned literatures, the parameter associated to nodes was discussed for some specific problems, but the correlativity between it and the parameter associated to arcs was not involved. There are no more comparisons between the two parameters and no further analysis to the algorithm's performance is made when applying different parameters. In this paper, the pheromone parameter which is associated to components is further discussed, which is called pheromone mark strategy. In the strategy, pheromones associate to the passed nodes instead of arcs on the construction graph, and the pheromone trace is formed by a series of scattered pheromone points called pheromone marks. Based on the strategy, an improved ACO called pheromone mark ACO (PM-ACO for short) is proposed whose pheromone update is based on the best-so-far tour rule integrated a r-best-node update rule and a relevant-node depositing rule.

3. Simple pheromone mark ACO

Considering a problem on the construction graph, if the pheromones are associated to the nodes, after the ants complete their tour constructions, pheromones are deposited on the traversed nodes. If the problem needs to cover all nodes in an iteration, the best path is a Hamiltonian cycle on the construction graph, and all nodes' pheromones can be updated in each iteration, thereby it is impossible to generate a differential pheromone density among different nodes. In this situation, PM-ACO equals to a greedy algorithm, and has nothing to do with the strength of pheromone marks. Therefore, the considered problem solved by PM-ACO should have the feature that the solution need not contain all the elements of the problem. Discussing it on the construction graph, the path should not be a Hamiltonian cycle. In this paper, the problems which have the above feature are called non-ergodic optimal problems. There are a lot of problems belonging to the non-ergodic optimal problem, such as the shortest path problem [18], robot path planning problem [19], knapsack problem [20] and so on. We take the shortest path problem into account to demonstrate the PM-ACO in this article because it is easy to be understood.

The prototype of PM-ACO is ACS, and it extends the classical ACO's pheromone mechanism and associates pheromones to the nodes but not to the arcs. When ants construct paths from the beginning node to the destination node, they generate pheromones and deposit them on the traversed nodes. After ants finish tours, a global pheromone update strategy is adopted to deposit pheromones on the nodes belonging to the best-so-far tour.

The major modifications based on ACS are as follows:

(1) The pseudorandom proportional rule is described as the following formula:

$$j = \begin{cases} \underset{l \in J_k(i)}{\operatorname{argmax}}[(\tau_l)^{\alpha} \times (\eta_{il})^{\beta}] & \text{if } q \le q_0 \\ J & \text{otherwise} \end{cases} \quad (1)$$

where j is the next node, α is the pheromone mark heuristic parameter, and τ_l is the pheromone mark strength on node l. β is the distance heuristic parameter, and η_{il} is a function generated by the distance of two nodes. q is a random variable uniformly distributed in [0,1], and q_0 $(0 < q_0 < 1)$ is a parameter.

(2) The transition probability between adjacent nodes is calculated as follows:

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_i^{\alpha} \times \eta_{ij}^{\beta}}{\sum_{u \in allowned}[\tau_i^{\alpha} \times \eta_{iu}^{\beta}]} & \text{if } j \in \text{allowned} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where P_{ij}^{k} is the transition probability of ant k from node i to node j.

(3) The global pheromone update strategy is defined as follows:

$$\begin{cases} \tau_i = (1-\rho) \times \tau_i + \Delta\tau_i^{g} + \Delta\tau_i^{r} + \Delta\tau_i^{s} \\ \Delta\tau_i^{g} = Q/L_{best} \end{cases} \quad (3)$$

where ρ is the pheromone evaporation rate, and $\Delta\tau_i^{g}$ is the pheromone increment of the node i caused by the best-so-far tour rule, and $\Delta\tau_i^{r}$ is the pheromone increment of the node