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A Novel Global Convergence Algorithm: Bee Collecting Pollen Algorithm*

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Abstract. Inspired by the behavior of the honeybees' collecting pollen, Bee Collecting Pollen Algorithm (BCPA) is proposed in this paper. This is a novel global convergence searching algorithm. It simulates the behavior of the honeybees' collecting pollen and describes the swarm intelligent. The experiment for TSP shows that the improve algorithm is more efficient.

Keywords: Honeybee, collect pollen, swarm intelligent, honey resource, global convergence.

1 Introduction

Swarm intelligence has gained increasingly high interest among the researchers from different areas, like, science, commerce and engineering over the last few years. It is particularly suitable to apply methods inspired by swarm intelligence to various optimization problems, especially if the space to be explored is large and complex.

Swarm Intelligence is an emerging field of artificial intelligence. It is concerned with modeling of social interactions between social beings, primarily ants, birds and, in the recent time, bees. This approach utilizes simple and flexible agents that form a collective intelligent as a group. This is an alternate approach to traditional intelligence models, exhibiting features of autonomy, emergence, robustness and self-organization. Several examples of artificial models inspired by interactions of social organisms are: Particle swarm optimization (PSO) methods, a population based stochastic optimization technique developed in 1995, by Eberhard and Kennedy [1].It is inspired by flocking behavior of the birds searching for food. Although PSO methods share many common attributes with GA, such as stochastic nature, population of solution candidates, PSO methods, unlike GA use a kind of cooperation between particles to drive the search process. PSO methods have no evolutionary operators like crossover and mutation. Each particle keeps track of its own best solution, and the best solution found so far by the swarm. It means the particles posses own and

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collective memory, and are able to communicate. The difference between global best and personal best is used to direct particles in search space. Another model of swarm-based approaches to optimization is Ant Colony Optimization (ACO), where the search process is inspired by the collective behavior of trail deposit and follow-up, observed by real ant colonies. A colony of simple (trial of pheromones) and thus proposes solution to a problem, based on their collective experience. Ant colony algorithms as evolutionary optimization algorithms were first proposed by Dorigo (1992) [2] as a multagent approach to different combinatorial optimization problems like traveling sales man problem and the quadratic assignment problem. Although, the first result were not very encouraging, it initiated the interest among research community, and since then, several algorithms have been proposed, some of them showing very convincing results.

A Classical Traveling Salesman Problem (TSP) has been an interesting problem. Given a number of nudes and their distances of each other, an optimal travel route is to be calculated so that starting from a node and visit every other node only once with the total distance covered minimized. As a special optimization problem ,there are many people have been do much work on it, i.e. Neural Network , Potential Fields, Genetic algorithms, Particles Swarm Optimization methods and other. Optimization methods can generally be classified into two distinct groups: direct search and gradient based search. Gradient based search techniques require derivative information of the function and constraints, while direct search methods use only objective function and constraint values. Since derivative information is not used, these methods generally require large number of iterations for convergence, but are at the other hand applicable to very broad problem space. However, TSP is inherently a NP hard problem with no easy solution.

The behavior of honey-bees shows many features like cooperation and communication, so honey-bees have aroused great interests in modeling intelligent behavior these years [3]-[19],but these algorithms are most mechanism by the marriage in bee. This paper describes a novel approach that uses the honey bees foraging model to solve the problem. Experimental results comparing the proposed honey bee colony approach with existing approaches such as ant colony and Genetic Algorithm (GA) will be presented.

This paper first describes how honey bee colonies deploy forager bees to collect nectar amongst diverse flower patches. The mapping of Traveling salesman problem to honey bee's forager deployment is given. Subsequently, the implementation details are discussed in section 3. This is then followed by a comparative study on the performance of the honey bee approach on benchmark problems in section4. The paper finally ends with conclusions and future works in Section 5.

2 Honey Bee Colony

Colonies of social insects such as ants and bees have instinct ability known as swarm intelligence. This highly organized behavior enables the colonies of insects to solve problems beyond capability of individual members by functioning collectively and interacting primitively amongst members of the group. In a honey bee colony for example, this behavior allows honey bees to explore the environment in search of flower patches (food sources) and then indicate the food source to the other bees of the colony when they return to the hive. Such a colony is characterized by self organization, adaptiveness and robustness.

Seeley (1995) proposed a behavioral model of self organization for a colony of honey bees. In the model, foraging bees visiting flower patches return to the hive with nectar as well as a profitability rating of respective patches. The collected nectar provides feedback on the current status of nectar flow into the hive. The profitability rating is a function of nectar quality, nectar bounty and distance from the hive. The feedback sets a response threshold for an enlisting signal which is known as waggle dance, the length of which is dependent on both the response threshold and the profitability rating. The waggle dance is performed on the dance floor where individual foragers can observe. The foragers can randomly select a dance to observe and follow from which they can learn the location of the flower patch and leave the hive to forage. This self organized model enables proportionate feedback on goodness of food sources [14].

3 Bee Collecting Pollen Algorithm

This section details algorithms to perform TSP inspired by the behavior of honey bee colony. The challenge is to adapt the self-organization behavior of the colony for solving TSP. There are two major characteristics of the bee colony in searching for food sources: waggle dance and forage (or nectar exploration).We will discuss in separate sub-sections on how we map these characteristics of a bee colony to TSP.

3.1 Waggle Dance

A forager f_i on return to the hive from nectar exploration will attempt with probability p to perform waggle dance on the dance floor with duration $D = d_i A$, where d_i changes with profitability rating while A denotes waggle dance scaling factor. Further, it will also attempt with probability r_i to observe and follow a randomly selected dance. The probability r_i is dynamic and also changes with profitability rating. If a forager chooses to follow a selected dance, it will use the 'path' taken by the forager performing the dance to guide its direction for flower patches. We term the path as 'preferred path'. The path for a forager is a series of landmarks from a source (hive) to a destination (nectar). For TSP, the profitability rating should be related to the objective function, which in our case, is make span. Let Pf_i denote the profitability rating for a forager, it is given by:

$$Pf_i = \frac{1}{C^i_{\max}} \tag{1}$$

where, $C^i_{\max}$ = make span of the schedule generated by a forager f_i.The bee colony's average profitability rating, Pf_{colony} is given by:

$$Pf_{colony} = \frac{1}{n} \sum_{j=1}^{n} \frac{1}{C^j_{\max}} \tag{2}$$

where, n = number of waggle dance at time t (we only consider those bees that dance when computing profitability rating); $C^{j}_{\max}$ = make span of the schedule generated by a forager f_j performing waggle dance. The dance duration, d_i is given by:

$$d_i = \frac{Pf_i}{Pf_{colony}} \tag{3}$$

The probability r_i of following a path is adjusted according the profitability ratings of a forager and the colony based on the lookup table 1 (adopted from Nakrani and Tovey 2004). Essentially, a forager is more likely to randomly observe and follow a waggle dance on the dance floor if its profitability rating is low as compared to the colony's.

Table 1. Look up Table for Adjusting Probability of Following a Waggle Dance

Profitability Rating	r_i
$Pf_i < 0.9Pf_{colony}$	0.60
$0.9Pf_{colony} \le Pf_i < 0.95Pf_{colony}$	0.20
$0.95Pf_{colony} \le Pf_i < 1.15Pf_{colony}$	0.02
$1.15Pf_{colony} \le Pf_i$	0.00

3.2 Forage (Nectar Exploration)

For foraging algorithm, a population of l foragers is defined in the colony. These foragers cyclically construct solutions to the TSP. The foragers move along branches from one node to another node in the disjunctive graph and so construct paths representing solutions. A forager must visit every node once and only once in the graph, starting from initial node (i.e. source) and finishing at final node (i.e. sink), so as to construct a complete solution. When a forager is at a specific node, it can only move to next node that is defined in a list of presently allowed nodes, imposed by precedence constraints of operations. A forager chooses the next node from the list according to the state transition rule:

$$P_{ij}(t) = \frac{[\rho_{ij}(t)]^{\alpha} \cdot [\frac{1}{d_{ij}}]^{\beta}}{\sum_{j \in allowed\_nodes} [\rho_{ij}(t)]^{\alpha} \cdot [\frac{1}{d_{ij}}]^{\beta}} \tag{4}$$

where, ρ_{ij} = rating of the edge between $node_i$ and $node_j$; d_{ij} = heuristic distance between $node_i$ and $node_j$; P_{ij} = probability to branch from $node_i$ and $node_j$;

The rating ρ_{ij} of the edge (directed) between $node_i$ and $node_j$ is given by:

$$\rho_{ij} = \begin{cases} \alpha \\ \dfrac{1 - m\alpha}{k - m} \end{cases}$$

where, α = value assigned to the preferred path, (α < 1.0); k = number of allowed nodes; m = number of preferred path, m = 1 or 0; Based on the expression, it should be noted that for the first nectar exploration expedition by the foragers, ρ_{ij} will be assigned the same value for all allowed nodes (since m = 0).The parameters α and β tune the relative importance in probability of the 'weight' in edges found in the preferred path versus the heuristic distance. According to this rule, edges that are found in the preferred path and that are shorter will have a higher probability to be chosen for the solution. The heuristic distance is the processing time of the operation associated with $node\ j$. When a forager completes a full path, the edges it has traveled and the make span of the resulting solution will be kept for the waggle dance when it returns to the hive.

3.3 The Disturbance from the Environment

There are many factors from the environment that influenced the bee's collect pollen. Meanwhile, when the best value keep on very little change, the algorithm should has gotten stuck in a local optimum to a certain degree. So there is a certain control in the algorithm. The bee's position will be changed by itself, given by added a random number.

3.4 The Death

A honey bee has only 6 weeks life. And in order to avoid premature, to stimulate the circle of individual turn the old and new and to reinforce the exploitation, a new population of bees will be introduced in each generation which could extend the search area in the algorithm.

3.5 The Bulletin

The Bulletin is used to record the best choice of all the bees. Each bee which has changed the position will compare with the bulletin. If the change one is better than the bulletin, the bulletin will be correct. This way can lead to the global search.

3.6 The Ending of the Algorithm

As an iterative algorithm, a good guideline of ending is needed. The max generation of 5 thousand is used to control the circle in the improved algorithm.

3.7 Algorithmic Framework

A combination of forage and waggle dance algorithms constitutes one cycle (or iteration) in this evolutionary computation approach. This computation will run for a specific number of iterations $N_{\max}$. The best solution during the iteration process will be presented as final schedule at the end of run. The algorithmic framework of the scheduling algorithm is presented in Algorithm 1.

Algorithm 1. Algorithmic framework for TSP
  for i = 1 to $N_{\max}$
  for j = 1 to 1
    Forage
    Save best solution
    Waggle dance
  if change little
    new population
  end if
end for
end for

4 Simulation

To test the global convergence searching performance of the algorithm, we use the TSP. Here TSP based on the data from TSPLIB is GA algorithm respectively. The results are showed by Figure 1 to Figure 4.

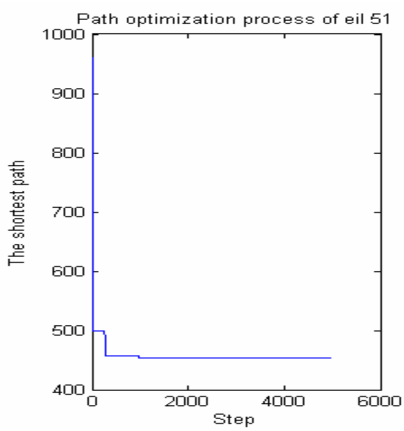


Fig. 1. Path optimization process of eil 51

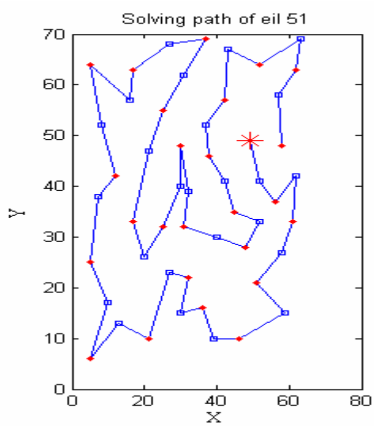
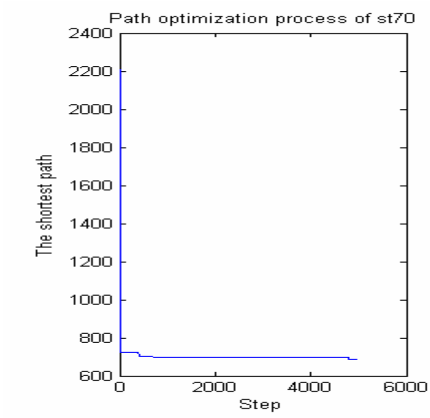


Fig. 2. Solving path of eil 51 nodes

(the best value as far is 426, our result is 434.3195)

Since the improved algorithm has great randomness, every parameter will be established by many times trial.By the experiment of NP hard problem TSP, improvement of the convergence rate has been greatly changed. Lower than 1 thousand generations, the improved algorithm will reach the global convergence point and the CPU time is less.



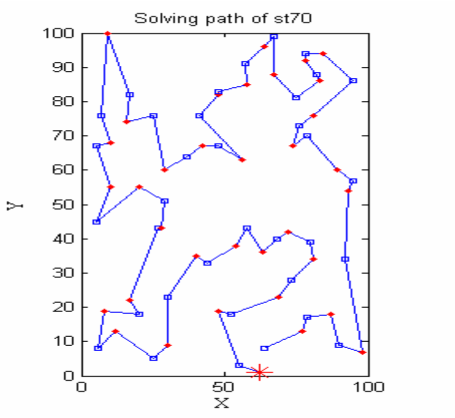


Fig. 3. Path optimization process of st70 **Fig. 4.** Solving path of st70 nodes

(the best value is 675, our result is 695. 4688)

5 Conclusions

A novel global convergence searching algorithm based on self-organization of honey bee colony has been implemented for solving TSP. It is found that the performance of the algorithm is comparable to ant colony algorithms, but gaps behind the efficient tabu search heuristics. Since the bee algorithm is our first implementation, we believe there is much room for improvement. We intend to test the bee algorithms on TSP. One of the works we intend to pursue is to deploy the algorithms in a distributed computing environment using software agents. Prior work has already been carried out using agents in symbiotic simulation of semiconductor assembly and test operation (Low et. al. 2005). In comparison to ant colony algorithms, it will be relatively easier to treat each bee forager as an agent in the bee colony algorithms since the issue of share state in maintaining a global pheromone table in ant algorithms does not occur.

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