IJITKM *Volume 6 • Number 2 • July-December 2013 pp. 165-169*

Improved Ant Colony System for Solving TSP

Neha [1], Baijnath Kaushik [2]
[1] Department of Computer science and Engineering, M.T.U Noida, INDIA
[2] Department of Computer science and Engineering, M.T.U Noida, INDIA
Neha.arya.24@ gmail.com, bkaushik99@gmail.com

Abstract
This study proposes a method for changing the values of the parameters used in finding probability to select the next city .This method is effective and outperforms the conventional Ant colony system This paper uses formulas to set the values of variables α, β and ρ where α and ρ are the pheromone updating parameters and β is the distance factor. These parameters have the direct influence on the performance of the algorithm. This paper has designed to provide optimal solution of travelling salesman problem by using the theory of ant colony optimization and adjusting the values of the influence parameters. The proposed method is therefore, an attractive method to find the shortest path for travelling salesman problem.

1. Introduction

As Ant colony optimization is a new meta-heuristic based on the behavior of real ants, this theory is applied on travelling salesman problem. This paper used this theory for solving travelling salesman problem and finding the optimal solution. Recently scientists have found models of social insect collective behavior and have been able to transform it into optimization and control algorithm. This is an algorithm to model the behavior of ants in establishing the shortest path from their nest to a food source and back by using an indirect form of communication. When ants move they release a chemical trail called pheromone on the route. Pheromone trail is used as distributed numeric information which is modified by the ants. Ants follow the trails to find its path. Ants will choose the path having the higher pheromone concentration with the higher probability. The first ant colony optimization algorithm which is named as "ant system" was proposed by Dorigo,Colorni and Maniezzo[2] to solve the well known travelling salesman problem

Travelling salesman problem is a classical problem in discrete or combinatorial optimization. In TSP a salesman wants to visit a number of cities to sell his product. The distance of every pair of cities is given .His Problem is, In what order the travel should so that he can visit every city exactly once and return back to the starting point by covering the shortest distance. That is he wants to construct a minimum weighted Hamiltonian circuit. The optimization goal is to find a shortest possible tour. TSP problem attracts computer scientists and mathematicians because it is easy to describe but difficult to solve.

2. Present Work

Ant colony optimization (ACO) is an evolutionary algorithm (EA) to model the behavior of almost blind ants in establishing the shortest path from their colony to their feeding sources and back .As ant moves , it lays varying amount of pheromones, which are detectable by other ants, along its path, thereby marking the path by a trail of such substances. We can solve Travelling salesman problem with the help of ACO.

2.1 ACO ALGORITHM FOR THE TSP

In TSP the optimization goal is to find a shortest possible tour. TSP can be solved using ACS [3]. The TSP can be taken as a graph of N cities and E edges. Let dij is the distance between city i and j and □ij the amount of pheromone in the edge that connects i and j. Each of m ants decides independently on the city to be visited next based on the intensification of pheromone trail □ij and a heuristic value ηij =1/dij is generally used. Each ant maintains a list of cities that remain to be visited. An ant located at city i selects an edge between city i and city j according to the probability

$$p_{ij}^{k} = \frac{[r_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum N_{l\epsilon N_i^k}[r_{ij}]^{\alpha}[\eta_{ij}]^{\beta}} \qquad (1)$$

Where the parameters and determines the relative influence of pheromone and distance. The above procedure is repeated until every ant has visited all of the cities. Then all ants move back to the initial cities.

PHEROMONE UPDATING

Local Pheromone Updating: During the construction of a tour , ants use a local updating rule to change the pheromone level of the edge (i, j) that they have traversed as

$$r(i,j) \leftarrow (1-\rho).r(i,j) + \rho.r_0 \tag{2}$$

where ρ is the local pheromone decay parameter, r_0 is the initial pheromone level.

Global Pheromone Updating: The global pheromone updating occurs once all ants have completed their tours. Only the edges (i, j) belonging to the best tour have the pheromone level updated as

$$r(i,j) \leftarrow (1-\alpha).r(i,j) + \alpha.\Delta r(i,j) \tag{3}$$

Where α is the global pheromone decay parameter.

The value of . $\Delta r(i,j)$ is determined by

$$\Delta r(i,j) = \begin{cases} \frac{1}{L_{ib}} & \text{if } (i,j) \epsilon \text{best tour} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Where Lib is the length of best tour found in this epoch.

2.2 ADJUSTING THE INFLUENCE PARAMETER

According to the above steps the pheromone decay parameters α and ρ and distance parameter β have direct influence on solution, construction and performance of the algorithm.

The global pheromone updating is intended to reinforce the shortest tour by depositing a good amount of pheromone on the corresponding edge .α is global pheromone decay parameter. If the value of α is too large, a great amount of pheromone will be added on the best tour edges in each epoch. On the other hand if the value of α is small, it will reduce the convergence rate and will improve the searching ability of the algorithm.

In contrast the local pheromone updating is done to make the edges less desirable for other ants. ρ is the local decay parameter .If the value of ρ is small the convergence rate become faster but if the value of ρ is larger, the evaporation rate will be higher and tour visited by ants will become weak.

If we put β=0 in equation (1), only pheromone amplification will work which leads a rapid convergence of stagnation situation which is strongly suboptimal. Hence a connection exists between the heuristic information and pheromone trail.

In traditional ant colony system algorithm the value of α, β and ρ are kept fixed throughout the optimization process. The following problems occurs by taking the fixed values of α , β and ρ:-

The best values of α and ρ depends on the instance. It may be possible that best setting values of α and ρ for one instance will not be as good for another instance.

The importance of Reinforcing the pheromone on a best tour yet is different to the decreasing the desirability of an edge during the optimization process.

If we increase the value of β it will increase the selection probability of the corresponding edge. So if the value of β will be changed with the corresponding edge it will increase the speed of the algorithm.

According to the above analysis if we proper values of α, β and ρ in different optimization state, it will help to find high quality tours and will accelerate the search speed. Hence we used dynamic values of influence parameters.

2.3 Adjusting the Values of α, β and ρ

Instead of using fixed values of α, β and ρ , we propose a method to adjust the values of influence parameters according the optimization state. When an ant starts travelling, the value of β changes according to the following Held Karp Lower Bound [4] Probability Selection Mechanism formula

$$\beta = B + \frac{d_{ij}}{L_1 + L_2 + d_{ij}} \tag{5}$$

Where B is a constant and set to be 5 that are suggested to be advantageous. L_1 is the length of sub-tour visited by ant and L_2 is the length of city unvisited by ant. This can be calculated by using Held-Karp lower bound method. d_{ij} is the length of the corresponding edge.

We can adjust the value of α and ρ by using Self Adaptive Ant Colony System [5]. In the initial state, a good amount of pheromone is deposited on the shorter tours, which attracts more ants to follow. So the value of α should be large and ρ should be small. On the other hand, the pheromone evaporation can weakened the shorter tour, so the value of ρ should be large and the value of α should be small. So it should be fruitful to adjust the values of α and ρ according to the optimization state.

Computation of the average tour similarity:
Step1) compute the similarity $S(T_k, T_{best})$ between tour of every ant and the best tour in the current iteration. K=1,2,3…….m where m is the number of ants.

$$S(T_k, T_{best}) = |T_k \cap T_{best}| \tag{6}$$

Because edges in a tour is equal to the number of cities so $S(T_k, T_{best}) \in \{0, 1, \ldots\ldots n\}$
Step2) Compute the Average Tour Similarity (ATS) according to the equation given by

$$ATS = \frac{1}{m}\sum_{k=1}^{m} S(T_k, T_{best}) \tag{7}$$

The normalized value of ATS is denoted by $\overline{ATS}$ and the value of

$$\overline{ATS} = ATS/n \tag{8}$$

Where $\overline{ATS}$ ranges from zero to one.

$$\alpha = a.\overline{ATS} \tag{9}$$

$$\rho = b.\overline{ATS} \tag{10}$$

In the initial state the value of $\overline{ATS}$ is small, so to accelerate the convergence speed we need large value of α and small value of ρ. On the other hand if value of $\overline{ATS}$ is small, we need small value of α and relatively large value of ρ.
According to the correlation between the parameter values, the value of a is negative while the value of b is positive.

3. Result and Discussion

In the proposed paper, we calculate the tour length of Improved Ant Colony System on the three symmetric instances, including eil51, eil76 and eil101 from the TSPLIB. Table 3.1 shows the optimal tour length of each instance.

Table 3.1

Instance	Number of cities	Tour length
eil51	51	420
eil76	76	531
eil101	101	621

3.1 Parameters and Settings

The following parameters are set the same for both Adaptive ACS and IACS for all of the instances: m=10, $\Gamma_0 = \frac{1}{n.L_{nn}}$ where L_{nn} is the tour length, computed by nearest neighbor method and n is the number of cities. Each instance is tested 100 times independently.

3.2 Results

The following snapshot show the optimum found for eil51, in which The following parameters are set as m=10, $\tau_0 = \frac{1}{n.L_{nn}}$ where L_{nn} is the tour length computed by nearest neighbor method and n is the number of cities and kept same for all instances. First snapshot shows in figure1 is the TSP generated for eil51, which contains 51 cities as nodes. The second snapshot shows in figure 2 is the optimum path found by the ants using optimal solution for travelling salesman problem using ant colony optimization method.

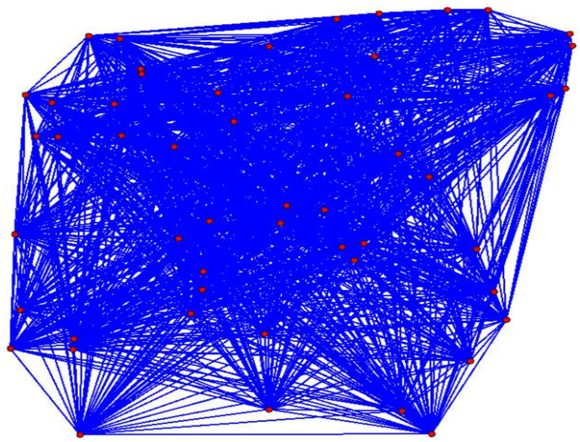

Figure 1: TSP generated for 51 cities

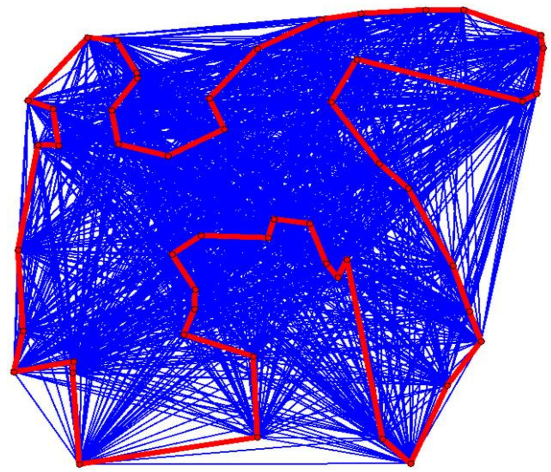

Figure2 optimal path found

3.4 COMPARISON

Figure 3 compares the cumulative frequency of obtaining the optimal solutions in 500 iterations of AACS with that of IACS. By figure3, one can observe that IACS searches the optimum solutions much faster than AACS on eil51 TSP instance.

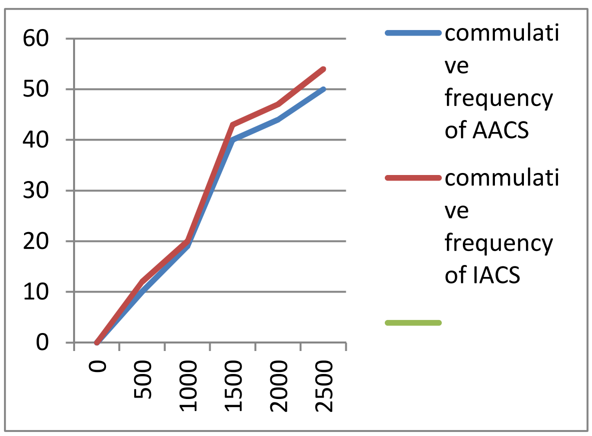

Figure3. X axis (number of epoch), Y axis (Cumulative frequency(AACS vs. IACS))

4. Conclusion

In this paper, an improved method to adjust values of the pheromone decay parameters α and ρ and distance parameter ρ for ACS has been proposed. The values of α and ρ are adapted to the Average Tour Similarity (ATS), which depends on the optimization state. The improved ACS (IACS) algorithm has been implemented and tested on benchmark TSP instances. The experimental results show that the proposed IACS algorithm gives better performance than the one with fixed pheromone decay parameters settings in terms of both the solution quality and the searching speed.

References

[1] M. Dorigo and T. Stützle, Ant Colony Optimization. Cambridge, MA: MIT Press, 2004.
[2] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," IEEE Trans. Systems, Man, and Cybernetics-Part B, vol. 26, no. 1, pp. 29-41, February 1996.
[3] M. Dorigo and L.M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," IEEE Trans. Evolutionary Computation, vol. 1, no. 1, pp. 53-66, April 1997.
[4] Lijie Li, Shangyou Ju, Ying Zhang "Improved Ant Colony Optimization for the Traveling Salesman Problem" International Conference on Intelligent Computation Technology and Automation. 2008.
[5] Wei-Yu, Xiao Hu and Jun Zhang Rui-Zhang Huang "Self-Adaptive Ant Colony System for the Traveling Salesman Problem" Proceedings of the 2009 IEEE International Conference Systems, Man, and Cybernetics San Antonio, TX, USA - October 2009.
[6] M. Dorigo and L.M. Gambardella, "Ant colonies for the traveling salesman problem," BioSystems, vol. 43, no. 2, pp. 73–81, 1997.
[7] L.M. Gambardella and M. Dorigo, "Solving symmetric and asymmetric TSPs by ant Colonies," in Proc. 1996 IEEE International Conference on Evolutionary Computation (ICEC'96), T. Baeck et al., Eds. IEEE Press, Piscataway, NJ, pp. 622–627, 1996.
[8] J. Zhang, X.-M. Hu, X. Tan, J.-H. Zhong, and Q. Huang, "Implementation of an ant colony optimization technique for job scheduling problem," Transactions of the Institute of Measurement and Control, vol. 28, no. 1, pp. 93-108, 2006.
[9] X.-M. Hu, J. Zhang, J. Xiao, and Y. Li, "Protein folding in hydrophobicpolar lattice model: a flexible ant-colony optimization approach," Protein & Peptide Letters, vol. 15, no. 5, pp. 469-477, 2008.
[10] X.-M. Hu, J. Zhang, and Y. Li, "Orthogonal method ant colony search for solving continuous optimization problems," Journal of computer science and technology, vol. 23, pp. 2-18, January 2008.
[11] Y. Lin, J. Zhang, and J. Xiao, "A pseudo parallel ant algorithm with an adaptive migration controller," Applied Mathematics and Computation, vol. 205, pp. 677-687, 2008.
[12] J. Zhang, W.-N. Chen, J.-H. Zhong, Xuan Tan, and Yun Li, "Continuous function optimization using hybrid ant colony approaches with orthogonal design scheme," SEAL'06, LNCS 4247, pp. 126-133, 2006.
[13] X.-M. Hu, J. Zhang, and H. Chung, "An intelligent testing system embedded with an ant colony optimization based test composition method," IEEE Trans. Systems, man, and Cybernetics-Part C. (in Press)
[13] Marco Dorigo, Mauro Birattari, and Thomas St¨utzle"Ant Colony Otimization" IEEE Computational Intelligence Magazine AntColony. November2006.
[14] D.S Johnson and L.A. McGeoch, "The Travelling salesman problem: a case study in localoptimization," in Local search in combinational optrimization, E.H.L Arts and J.KLenstra(Eds),NewYork:Wiley and sons,1997
[15]M. Dorigo, V. Maniezzo, and A. Colorni, "Positive feedback as a search strategy," Dipartimento di Elettronica, Politecnico di Milano, Italy, Tech. Rep. 91-016, 1991.
[16] M. Dorigo, "Optimization, learning and natural algorithms (in italian)," Ph.D. dissertation, Dipartimento di Elettronica, Politecnico di Milano, Italy, 1992.
[17] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant System: Optimization by a colony of cooperating agents," IEEE Transactions on Systems, Man, and Cybernetics—Part B, vol. 26, no. 1,pp. 29–41, 1996.
[18] T. St¨utzle and H.H. Hoos, "MAX–MIN Ant System," Future Generation Computer Systems, vol. 16, no. 8, pp. 889–914, 2000. [19] K. Socha, J. Knowles, and M. Sampels, "A MAX–MIN ant system for the university timetabling problem," in Proc. ANTS 2002, ser. LNCS, M. Dorigo et al., Eds., vol. 2463, p. 1,Berlin, Germany: Springer Verlag, 2002.