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Ant System Initial Parameters Distribution

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Introduction

Majority of the world problems are of optimization type. Various optimization techniques are widely used to solve these problems.

Most typical and widely known combinational optimization problem is the Traveling Salesman Problem (TSP) [1]. TSP is usually included as a part of a testing set for evaluation of performance of optimization algorithms.

With advanced in parallel processing, popularity of multi-agent algorithms in various fields [2] is boosting. Ants' ability to find shortest paths is a basis for Ant Colony Optimization (ACO) [3] family of nature inspired multi-agent optimization algorithms. This field is growing and each year new modifications and applications are presented.

ACO can be applied to a wide range of combinatorial optimization problems. In fact ACO is applicable to various fields like vehicle routing [4], image pre-processing [5], embedded systems application [6] and many other.

Quick evolving embedded systems provide means of implementing various complex algorithms like speech recognition [7] in small sized specialized packages with relatively high processing speed.

The main problem is that ACO algorithms use a set of initial parameters, and the result of optimization is highly parameter dependent. Often the range of initial values for the parameters is provided [3] for each type of algorithm, but in reality it is often impossible to check all possible values, especially when talking about embedded systems that are usually more limited on processing power, compared to full sized computers, and trying various sets of parameters may lead to rather lengthy computations even on fast machines.

Many papers suggest adapting values during simulation by the use of other optimization techniques [8], like genetic algorithms [9] and tabu search [10] with better results than parameters value selection by hand. Despite of effectiveness this approach increases the complexity of the ACO algorithm, and adaptation also requires some initial parameters which are problem dependent.

In this paper initial results on Ant System (AS) [11] parameter values distribution among ants, so that ant caries unique set of parameter values, are presented. Comparison is based on solving different TSP problems with different parameter sets.

The work starts with short description of AS optimization algorithm by presenting main formulae and describing initial parameters. Next, experimental setup for testing initial parameter values distribution is presented. At the end the experimental results are provided together with the conclusions.

Ant System

There are two main steps in ant-cycle version of AS: tour construction and pheromone update. According to recommendations [3] it is useful to initialize pheromone trails on arcs connecting cities to a small value:

$$\tau_{ij} = \tau_0 = m / C^{\mathrm{nn}}, \quad \forall(i, j), \tag{1}$$

where τ_{ij} is pheromone value on an arc from city i to city j; τ_0 is the initial pheromone value; m is a number of ants; C^{nn} is the length of a tour generated by the nearest-neighbor heuristic (simple algorithm of choosing the nearest city until tour is constructed). Small value of τ_0 causes AS to converge quickly to a solution that is biased by initial tours, high value of τ_0 increases search time, as iterations are lost for pheromone evaporation.

In AS the number of ants m is usually equal to the number of cities n, so during initialization ants are placed one in each city. Each iteration, ants are moved until tours are fully constructed. Ants' decision to which city to move next is based on random proportional rule. Movement probability of ant k from city i to city j could be calculated by

$$p_{ij}^k = \frac{\left[\tau_{ij}\right]^\alpha \left[\eta_{ij}\right]^\beta}{\sum_{l \in N_i^k} \left[\tau_{il}\right]^\alpha \left[\eta_{il}\right]^\beta}, \quad \text{if } j \in N_i^k, \tag{2}$$

where $\eta_{ij} = 1/d_{ij}$ is a heuristic information based on distance d_{ij} between cities i and j; α determines influence of pheromone trail; β determines influence of heuristic information; N_i^k is the feasible neighborhood (non-visited cities) of ant k while being at city i. With $\beta = 0$, only pheromone value has an influence on ant movement and causes rather poor results, especially when $\alpha > 1$. High α values cause all ants to follow the same path without search for better solution.

For the ant k to remember already visited cities a memory M^k is required, where the list of visited cities is stored. Memory also allows length calculation of the tour T^k constructed by ant k and pheromone deposition.

After all ants have constructed their tours, the pheromone trails could be updated. At first pheromone should be evaporated from all arcs

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad \forall (i,j) \in L, \tag{3}$$

where $0 < \rho \le 1$ is the pheromone evaporation coefficient. Evaporation is required to avoid unlimited accumulation of pheromone and thus to decrease the probability of choosing arcs that led to far from optimal solutions.

After evaporation, all ants deposit pheromone on the arcs from the tour constructed

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k, \quad \forall (i,j) \in L, \tag{4}$$

where $\Delta\tau_{ij}^k$ is the amount of pheromone ant k deposits on visited arcs

$$\Delta\tau_{ij}^k = \begin{cases} 1/C^k, & \text{if arc } (i,j) \text{ belongs to } T^k; \\ 0, & \text{otherwise;} \end{cases} \tag{5}$$

where C^k is the length of the tour T^k, calculated as sum of the lengths of all arcs from the tour. So, the shorter the tour found the higher the pheromone level will be.

Distributing parameters

According to the recommended initial parameters values [3], β could be any value in a given range from 2 to 5. It is possible to choose a step size and try every value from the range to determine the best suitable, however it is not practical as it will take a long time. Each value will require many solutions of the same problem for statistical proof.

AS is a multi-agent optimization algorithm based on nature and in nature all living creatures are different, naturally, each ant from the AS should have a different unique set of parameters.

As recommended parameters are equally possible from the range, a value of β is distributed uniformly among ants and could be expressed by

$$\beta^k = \beta_{\min} + \Delta\beta \cdot (k-1), \tag{6}$$

where β^k is a heuristic information sensitivity of ant k; $\Delta\beta$ is a step, expressed by

$$\Delta\beta = \frac{\beta_{\max} - \beta_{\min}}{n}, \tag{7}$$

where $\beta_{\max}$ and $\beta_{\min}$ are maximum and minimum recommended values for β.

Another tried distribution of heuristic information sensitivity is of Gaussian type. In this case values of β could be approximated by

$$\beta^k = \left(\ln\left(\frac{d^k}{1-d^k} \right) / 9.2 + 0.5 \right) \cdot (\beta_{\max} - \beta_{\min}) + \beta_{\min}, \tag{8}$$

where $d^k = (k-1)/(m-1) \cdot 0.98 + 0.5$.

Experimental setup

For experimental testing, problems with known solutions are needed so it is easy to check effectiveness of the algorithm.

TSPLIB [12] database has a set of various sizes TSP. Three symmetrical TSP were chosen: one small problem burma14, and two average problems att48 and berlin52. Knowing, that AS is not the fastest technique for TSP solving, and keeping in mind that for each parameter change 100 experiments are needed, larger TSP were not considered.

According to recommendations [3], these parameters were chosen: $\alpha = 1$; $\rho = 0.5$; $m = n$; $\tau_0 = m / C^{\mathrm{nn}}$. In the case of β parameter, a uniform distribution was used with values $\beta_{\min} = 2$; $\beta_{\max} = 5$.

During experiment e, the iteration t error was calculated according to

$$E_t^e = \left(1 - \frac{C^{\mathrm{opt}}}{C_t^{\mathrm{fnd}}} \right), \tag{9}$$

where C^{opt} is the known distance of the optimal tour from TSPLIB database; $\forall(k),\ C_t^{\mathrm{fnd}} = \min C_t^k$ is the iteration best distance found by AS during iteration t. Because of 100 experiments for each parameter's set, the mean error of each iteration could be defined

$$\overline{E}_t = \frac{1}{100} \sum_{100}^{e=1} E_t^e, \tag{10}$$

For each problem 300 iterations were performed. For each iteration the mean and minimum mean $\forall(t),\ \overline{E}_{\min} = \min\left(\overline{E}_t\right)$ errors were calculated.

Table 1. Results of TSP solving with different parameters sets

Problem	Berlin52		Att48		Burma14	
Sensitivity to heuristic information, β	Minimum mean error reached	Optimal solutions found	Minimum mean error reached	Optimal solutions found	Minimum mean error reached	Optimal solutions found
2.0	0.0774	15	0.0858	0	0.0345	**97**
3.0	0.0679	19	0.0720	1	0.0283	38
3.5	**0.0660**	**31**	0.0699	**3**	0.0269	15
4.0	0.0683	5	0.0679	1	**0.0267**	11
5.0	0.0712	1	**0.0669**	1	0.0268	1
Unif[2:5]	0.0673	16	0.0686	1	**0.0267**	19
Gauss[2:5]	0.0673	21	0.0678	2	0.0278	10

Results

Experimental results, presented in Table 1, reflect an overall performance of AS with different parameter sets. Minimum mean error reached during 300 iterations could be interpreted as good measure of overall algorithm performance. It points to algorithm's ability to provide consistent results that are in most cases acceptable. Number of optimal solutions found is taken from 100 experiments and points out to algorithm's ability finding optimal solutions. The more often algorithm finds optimal solution, the better parameter values were chosen.

First problem tested, was Berlin52. By testing possible heuristic information sensitivity parameter values it was determined, that when $\beta = 3.5$, the algorithm has reached the lowest minimum mean error and also was able to find the highest number of optimal solutions. Comparing obtained results with uniform and Gaussian distributions of β values, it could be seen that despite negligible difference in minimum mean error, about 1 %, the difference in number of optimal solutions found is about 2 times for uniform distribution and about 1.5 times for Gaussian. Gaussian gain over uniform distribution could be explained by the fact, that optimal value of β is right in the center of distribution, so there exist more ants with parameters close to optimal.

Next problem is Att48. Here the behavior of algorithm is bit different. As the optimal value of β is still close to 3.5, but the number of optimal solutions found is very small. That could be explained by either far from optimal other parameters values or rather complex optimization problem. Uniform distributed values yielded 3 times less and Gaussian distributed 1.5 times less optimal solutions. Minimum mean error is low and similar to one achieved in Berlin52 case.

Burma14 is a small problem where the optimal value of β is off the center and close to 2.0. Here the uniform distribution of parameter values results in 2 times more optimal solutions than in case of Gaussian parameter values distribution and 5 times less compared with the optimal. The difference between distributed parameter values and minimal mean found is again negligible. Also smaller problems result in smaller number of ants and bigger difference between unique parameter values sets.

Of course, when analyzing results, it should be taken into account, than initial parameter values are not known.

Table 2. Convergence speed of AS

Problem	Berlin52	Att48	Burma14
Sensitivity to heuristic information	Iteration, at which nearest neighborhood algorithm error was reached by AS		
2.0	11	9	**1**
3.0	7	6	**1**
3.5	6	4	**1**
4.0	5	3	**1**
5.0	**2**	**1**	**1**
Unif[2:5]	5	4	**1**
Gauss[2:5]	6	4	**1**

Convergence speed of AS with different parameters values is analyzed based on nearest neighbor algorithm. Nearest neighbor algorithm is simple and cost effective way to find acceptable solution of TSP. In the Table 2 the number of iterations required for mean error to reach the nearest neighbor algorithm error level is presented. The lower the number of iterations to reach the nearest neighbor error the better the convergence speed.

Burma14 problem may be an exception, because of its small size. Here just one iteration is required for AS to reach the nearest neighbor level regardless of initial parameter value. Berlin52 and Att48 are more realistic problems and convergence speed is highly dependent on initial parameters set. The highest convergence speed is expected when algorithm heavily relies on heuristic information ($\beta = 5.0$). In case of uniform and Gaussian distributions the convergence speed remains close to the average (about 3 times better than the worst and 3 times worse than the best).

Conclusions

1. Uniform distribution of AS possible initial parameter values among ants proved to be reasonable choice when exact parameters values are not known and is suitable for embedded application without increase of algorithm complexity.
2. Minimum mean error reached is competitive with the optimal parameters AS with the difference not more than 2 % and similar convergence speed.
3. The rate of successful optimal solution search is from 2 to 5 times worse from optimal due to small number of ants with close to optimal parameters set.

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The paper presents some preliminary results on distributing initial parameter values among ants in Ant System. Two cases are studied, one with uniform distribution of heuristic information sensitivity values among ants and other with Gaussian distribution. Experimental analysis is performed by comparing behavior of Ant System with possible parameter values from the range to distributed parameter values solving Traveling Salesman Problem. Minimum mean error found, number of optimal solutions found and convergence speed are used as main indicators of Ant System performance evaluation. Uniform distribution proved to have minimum mean error difference from optimal value not more than 2 % with similar convergence speed. Number of optimal solutions found is from 2 to 5 times worse than in case of optimal parameter value due to small number of ants with parameter set close to optimal. Distribution of initial parameter values proved to be competitive when system complexity increase is not possible and initial values are not known. Bibl. 12, tabl. 2 (in English; abstracts in English and Lithuanian).

R. Laptik. Skruzdžių sistemos pradinių parametrų paskirstymas // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2011. – Nr. 4(110). – P. 85–88.

Straipsnyje pateikiami pirminiai pradinių parametrų verčių paskirstymo skruzdėms skruzdžių sistemoje rezultatai. Analizuojami du parametrų paskirstymo atvejai: vienas tolydaus skirstinio, kitas – Gausso. Eksperimentiniu tyrimu sprendžiama keliaujančio prekeivio užduotis, lyginant skruzdžių sistemos elgseną esant skirtingoms parametrų vertėms iš intervalo ir skruzdėms paskirstytoms vertėms. Minimali vidutinė klaida, surastų optimalių sprendinių skaičius ir konvergavimo greitis naudojami kaip skruzdžių sistemos našumo indikatoriai. Tolydus parametro verčių paskirstymas leido pasiekti minimalią vidutinę klaidą, kai skirtumas ne daugiau kaip 2 % nuo optimalios parametro vertės esant panašiam konvergavimo greičiui. Rastų optimalių sprendinių skaičius nuo 2 iki 5 kartų mažesnis nei esant optimaliai parametro vertei, nes, esant paskirstytoms parametro vertėms tik nedidelis skaičius skruzdžių turi parametrų rinkinį, artimą optimaliam. Paskirstyti pradinio parametro vertes tikslinga, kai neįmanoma didinti sistemos sudėtingumo ir pradinės parametrų vertės nėra žinomos. Bibl. 12, lent. 2 (anglų kalba; santraukos anglų ir lietuvių k.).