APPLICATION OF ANT COLONY OPTIMISATION ALGORITHM ON THE RECURSIVE PROPAGATION MODEL FOR URBAN MICROCELLS

Pavel Pechač

Czech Technical University in Prague, Dept. of Electromagnetic Field
Technická 2, 166 27 Praha 6, Czech Republic
E-mail: pechac@ieee.org

ABSTRACT

Ant Colony Optimisation algorithm - a multi-agent approach to combinatorial optimisation problems - is used for a simple ray tracing performed on only an ordinary bitmap of the city map. Together with the Berg's recursive model a non-line-of-sight path loss could be calculated without any need of building database. In this way the coverage predictions for urban microcells could become extremely easy and fast to apply.

INTRODUCTION

Microcellular structure is mostly demanded for wireless personal communication systems, such as UMTS. Empirical propagation models widely used in macrocells cannot be utilized in microcells. The nature of wave propagation in urban microcells requires different approach. Mostly the deterministic ray tracing techniques were adopted. While the results of the deterministic modelling are excellent (precision, wide-band outputs) the input requirements are very extensive. Building database including electrical parameters of used materials has to be defined. The ray tracing algorithms are very complex and time consuming. That is why there is a challenge to explore alternative ways of the signal propagation prediction. One of the models is the recursive model [1]. The idea is based on a very simple two-dimensional ray tracing in a plan view of the city microcell. But still, the basic necessity to trace the ray could be the input vector data describing a position and shape of buildings in the urban scenario. The idea presented in this paper is to enable a very simple ray tracing performed on only a common bitmap - scan of the city map. Untraditional technique for this kind of problem was used - Ant Colony Optimisation [3], which is a multi-agent approach to combinatorial optimisation problems.

RECURSIVE MODEL

Semi-deterministic approach for street microcells - the recursive model - was introduced by J-E. Berg [1]. The model does not require knowledge of building materials but only a two dimensional building database is needed. The shortest path along streets is determined among buildings between a base station and a mobile antenna. A simple geometrical ray tracing technique can be used. The path is break down into a number of straight segments interconnected by nodes. The "illusory" distance is obtained recursively as function of a real length of segments and an angle of segments crossings in nodes. It means each time the path bends the illusory distance is lengthened. Then a simple empirical formula is applied on the illusory distance to calculate the total path loss. A detailed description of the model can be found in [1]. The model was also included to [2].

ANT COLONY OPTIMISATION

Ant Colony Optimisation was proposed by Dorigo [3]. This multi-agent approach can be used for various combinatorial optimisation problems. The algorithms were inspired by the observation of real ant colonies. Ants are social insects living in colonies with interesting foraging behaviour. In particular, an ant can find shortest paths between food sources and a nest. While walking from food sources to the nest and vice versa, ants deposit on the ground a substance called pheromone, forming a pheromone trail. Ants can smell pheromone and, when choosing their way, they tend to choose paths marked by strong pheromone concentrations. It has been shown that this pheromone trail following behaviour employed by a colony of ants can give rise to the emergence of shortest paths. This phenomenon is explained in Fig. 1.

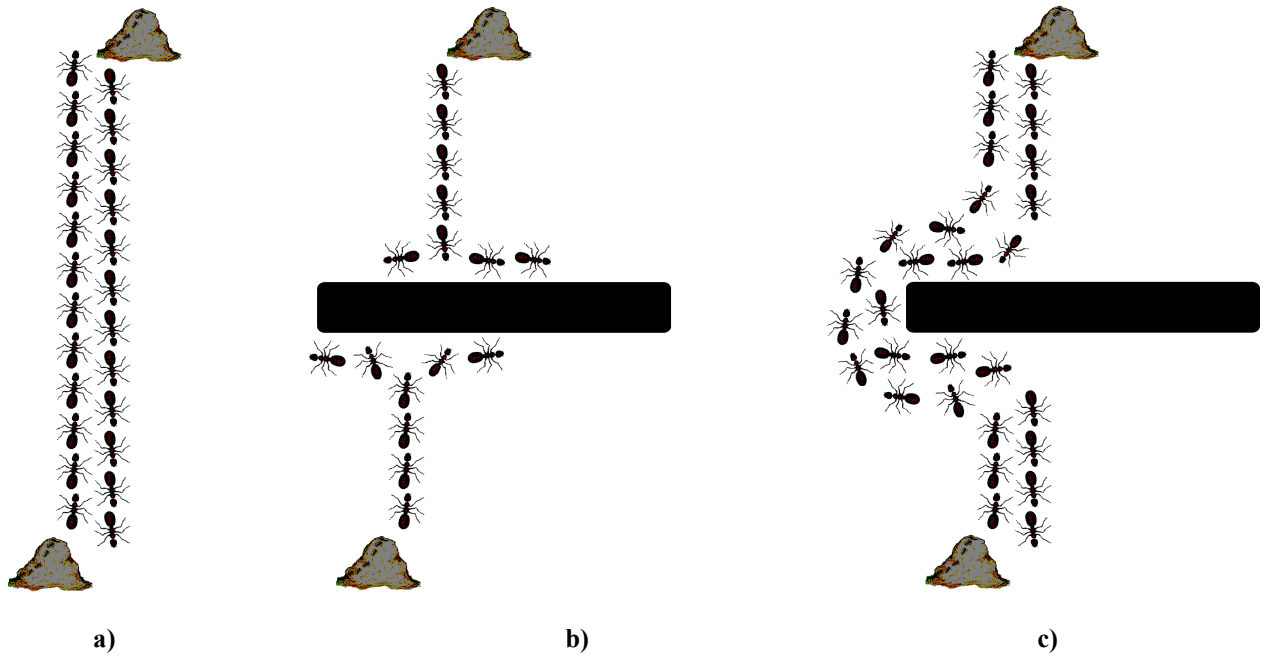


Fig. 1. Basic principles of Ant Colony Optimisation: ants searching the shortest route using a pheromone trail

In Fig. 1a ants walk between two points via unobstructed path. When an obstacle breaks the path (Fig. 1b) ants try to get around the obstacle randomly choosing either way. If the two paths encircling the obstacle have the different length, more ants pass the shorter route on their continuous pendulum motion between the nest points in particular time interval. While each ant keeps marking its way by pheromones the shorter route attracts more pheromone concentrations and consequently more and more ants choose this route. This feedback leads soon to final stage in Fig. 1c, where entire ant colony uses the shortest path. There are many variations of the ant colony optimisation applied on various classical problems. Many references can be found in [4].

ANT COLONY SYSTEM (ACS) ALGORITHM

Slightly modified algorithm called Ant Colony System [5] originally designed for Travelling Salesman Problem was adopted. Let us assume a graph $G = (N, A)$ with N being set of nodes and A the set of arcs connecting the nodes. The algorithm searching the shortest path between nodes N_1 and N_2 can be outlined in following steps:

1. All arcs are initialised with small amount of pheromone τ_0, which is an inverse line-distance between N_1 and N_2.

2. An ant is launched from N_1 pseudo-randomly walking from a node to node via connecting arcs as far as the N_2 or dead end is reached. While deciding which arc to go from a node, each i-th arc leading from the node is assigned a probability for its selection:

$$p_i = \frac{\tau_i \eta_i^{\beta}}{\sum_i \tau_i \eta_i^{\beta}} , \tag{1}$$

where τ_i is the pheromone concentration on the i-th arc, η_i is an a priori available heuristic value for the i-th arc (inverse length of the arc plus the line-distance between appropriate node and N_2), and β is a parameter determining the relative influence of the heuristic information. The previously visited arcs are excluded from the selection. Then a random number q between 0 and 1 is generated. If $q < q_0$, where q_0 is another parameter of the algorithm, the arc with the highest p_i is selected. Otherwise random selection of the arc based on the probability distribution (1) is accomplished. After having crossed the i-th arc during the tour construction a local update rule is immediately applied to the pheromone concentration:

$$\tau_i = (1-\rho)\,\tau_i + \rho\tau_0 , \tag{2}$$

where ρ is a parameter ($0 \le \rho \le 1$). The effect of the local updating rule is to make already chosen arc less desirable for a following ant. In this way more route variations can be explored.

3. The previous step is performed for a colony of C ants. Then the most successful ant - the ant with the shortest route from N_1 to N_2 - is selected to update the pheromone trails. All arcs of the graph G are updated using global update rule:

$$\tau_i = (1-\alpha)\,\tau_i + \alpha\tau_L \ , \tag{3}$$

where α is a parameter ($0 \le \alpha \le 1$) determining the evaporation of pheromone concentrations and τ_L is a value inversely proportional to the path length of the best solution in case of an arc visited by the best ant or zero for all other arcs. There are two different ways to choose the ant that is allowed to perform the global updating. In the "global-best" method only the ant that did the shortest route since the very beginning of the optimisation process is selected. In the "iteration-best" method always the best ant from the colony deposits the pheromones despite of previous iterations. In all simulations presented in this paper "iteration-best" strategy was applied.

4. Steps 2 and 3 are repeated for a fixed number of iterations or as long as the desired solution is reached. After stopping the algorithm the pheromone trail in the graph G or stored solution of the very best ant should indicate the shortest path between N_1 and N_2.

ADAPTED ACS ALGORITHM FOR RAY TRACING IN MICROCELL

First, the graph G must be defined to perform the ACS. The graph can be easily constructed using a grid applied on a pixel bitmap of an urban scenario (e.g. scan of a city map). Arcs interconnect all grid points - nodes of the graph - one with each other. Using simple raster graphics procedures all the nodes and arcs interfering with filled elements, which represent buildings or other obstacles, are eliminated. The density of the nodes determines memory and computation time demands of the optimisation process. Examples of the graph generation for two different nodes densities are illustrated in Fig. 2. If necessary the graph can be fined down as far as the nodes correspond to bitmap pixels.

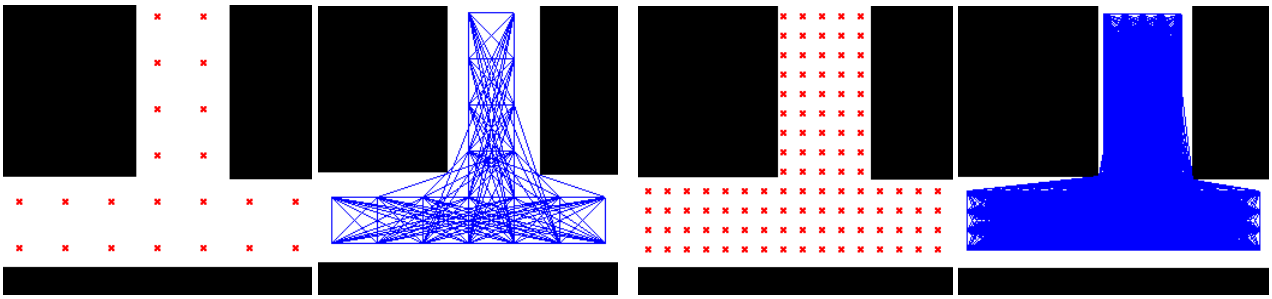
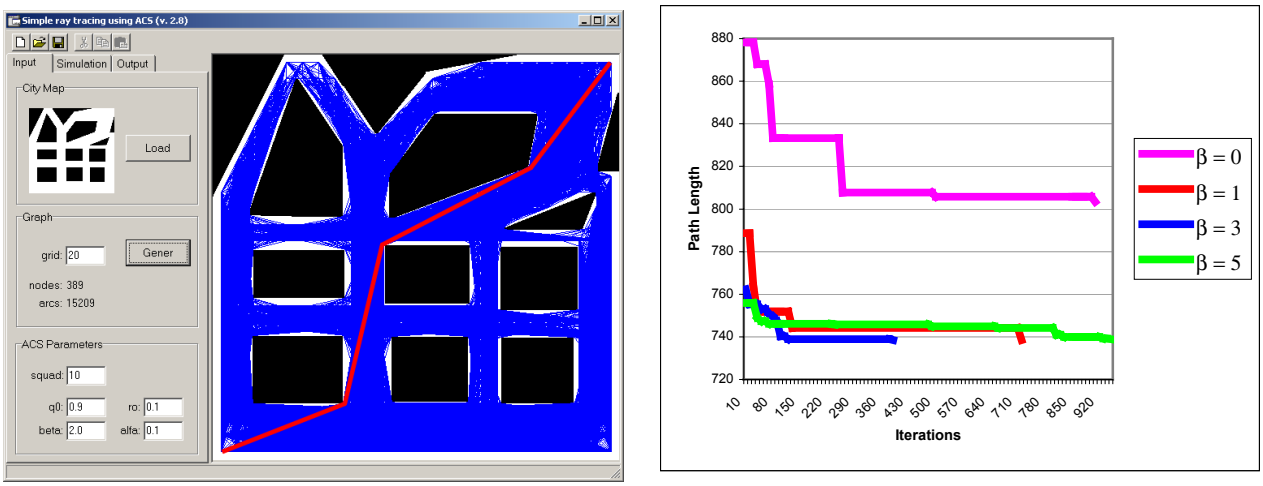


Fig. 2. Examples of graph generation with two different nodes densities in a bitmap representing a city map (red - nodes, blue - arcs)

As shown above there are five basic parameters controlling the ASC algorithm: number of ants C, q_0 and β for pseudo-random route selection in (1), ρ for the local update rule in (2), and α for the global update rule in (3). A software tool was developed to test and evaluate the algorithm. An example of a screenshot is shown in Fig. 3a. As default starting values the parameters from [5] were used: C = 10, q_0 = 0.9, β = 2.0, ρ = 0.1, and α = 0.1. Large set of different parameters was tested on simple scenarios to find the optimal values for our kind of problem. Following values were established as the optimum: C = 50, q_0 = 0.5, β = 3.0, ρ = 0.2, and α = 0.2.

The heuristic information η_i together with the parameter β from (1) was found of crucial importance for the algorithm. Results of the search process for four different sets of parameters are shown In Fig. 3b. In this case the influence of β is demonstrated. For β = 3 the global solution was found very quickly. When the value is significantly increased (β = 5) or decreased (β = 1) the same solution is reached, but the algorithm convergence is much slower. It can be seen that for β = 0, which means the heuristic information η_i in (1) is completely ignored, the global optimum was not found at all. Other parameters were not so fundamental for the optimisation. For instance, the number of ants C = 50 is a compromise: the higher is the value of C the higher is the certainty that the global solution will be found, but, at the same time, the longer is the computation time.



a) **b)**

Fig. 3. a) A screenshot of the software simulation tool for the ACS algorithm testing, b) the shortest path search process for four different sets of parameters: $C = 50$, $q_0 = 0.5$, $\beta = 0.0$, 1.0, 3.0, and 5.0, $\rho = 0.2$, $\alpha = 0.2$

When the desired shortest segmented path along streets is found using the ACS algorithm, the non-line-of-sight path loss could be calculated using simple formulas of the recursive model [1].

CONCLUSION

New algorithm for coverage predictions in microcells, which is based on two techniques originated in very different fields of application, was presented. Ant Colony Optimisation together with the Berg's recursive model enables non-line-of-sight path loss calculations without any need of building database.

As indicated above, first simulations for simple urban scenarios proved a very promising efficiency of the algorithm. The work continues tuning and evaluating the method on more complex scenarios. There are also some enhancement possibilities for the algorithm. One of the techniques is a "local search" applied to ant's route to deterministically optimise the route during the iterations. In addition, when a propagation time instead of the path length is treated, the algorithm can be used for a ray tracing in inhomogeneous environments with different permitivities. Development carries on the software tool introduced above as well. Obviously there are other propagation prediction applications where the presented ACS algorithm can be utilised instead of classical ray tracing.

ACKNOWLEDGEMENTS

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REFERENCES

[1] J-E. Berg, "A Recursive Method for Street Microcell Path Loss Calculation," *Proceedings IEEE International Symposium on Personal, Indoor and Mobile Radio Communications PIMRC'95*, vol. 1, pp. 140 - 143, 1995.
[2] ETSI technical report TR 101 112, "Selection procedures for the choice of radio transmission technologies of the UMTS," ETSI, 1998.
[3] M. Dorigo, V. Maniezzo, and A. Colorni, "The Ant System: Optimization by a Colony of Cooperating Agents," *IEEE Transactions on Systems, Man, and Cybernetics Part B*, vol. 26, vol. 1, pp. 1 - 13, 1996.
[4] T. Stützle, M. Dorigo, „ACO Algorithms for the Traveling Salesman Problem," In *K. Miettinen, M. Makela, P. Neittaanmaki, J. Periaux, editors, Evolutionary Algorithms in Engineering and Computer Science*, Wiley, 1999.
[5] M. Dorigo, L. M. Gambardella, "Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, pp. 53-66, 1997.