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Sensor Network for Monitoring

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Abstract: *Sensor networks are widely used nowadays. They can be used with various applications, such as monitoring, tracking, communication, and many more. The positioning of the sensors in the network is of great importance. It should enable full coverage, communication between sensors, and transmission of collected data. On the other hand, it is important to do this with as few sensors as possible. When the network is used for monitoring, it is important to consider the presence of impenetrable obstacles. They cover part of the coverage area of some of the sensors. This requires a different positioning of the sensors compared to the case without obstacles. For the solution, we propose an algorithm based on Ant Colony Optimization (ACO) methodology. We have shown how the algorithm works, when there are impenetrable obstacles in the observed space. Using the obstacles, areas of arbitrary shape can be modeled.*

Keywords: *Ant colony optimization, Sensor network deployment, Combinatorial optimization.*

1. Introduction

Sensors are devices that collect and transmit data. The collected data can be very diverse and depend on the specific application and the goals set. There are simpler sensors that respond and therefore collect only one type of data. This can be: movement; chemical substance; smoke; illumination; humidity; the content of certain particles, and others. Others respond to several types of data and also transmit images. Sensor networks (wired and wireless), have a large practical application. Their ability to monitor large areas, react in real time, and be relatively simple to use is the reason for their increasing use. Sensor networks are applied in many fields. In the military for reconnaissance, surveillance and acquisition of targets [1]. In nature to monitor forest fires [2]. In geophysics for the study of volcanic eruptions [3] and seismic activity monitoring [4]. In civilian life for monitoring objects such as stations, airports, large stores [5], building wireless communication networks such as cellular phones [6], etc.

The application of sensor networks can be classified of nature of their use to following classes: environmental [7, 8]; flora and fauna [9, 10]; industrial [11-13];

urban [14, 15]; military [16, 17]; structural health [18]; automotive sensor networks [19]; sensor networks in avionics [20], etc.

Their use is growing daily, and their potential seems limitless. When building a sensor network, sensor positioning is of great importance. Directly dependent on it are the coverage provided by the network and the number of sensors, on which the economic price of the network depends.

When monitoring small areas such as rooms, offices, etc., it is sufficient to place several cameras, monitoring the places, from which the room can be entered. When the monitored object has a large area, then the problem is different. In this case, the entire area of the object must be monitored. The presence of obstacles should be taken into account. The goal is to have no area deprived of monitoring.

In this article, we have focused on the optimal placement of indoor sensors, in particular cameras, for monitoring large spaces. These could be train stations, airports, large shopping centers, etc. Full coverage of the target area is important and is the most critical problem in implementing sensor networks [23]. Various sensor positioning techniques are discussed in [21]. It is not advisable to use random sensor placement. This can leave some areas uncovered, while others will be covered by unnecessarily many sensors. Other authors place sensors in a random way till all area is covered. After they try to remove part of the sensors without disturbing the coverage and thus decreasing their number [22]. This approach is not efficient. Sensor positioning methods can be grouped into three main groups: classical techniques, metaheuristics, and self-scheduling.

In the group of classical techniques are force-based techniques [24], grid-base techniques [25], and Computational Geometry-Based Techniques [26].

The group of metaheuristics consists of Genetic algorithm [27], Simulated annealing [28], Artificial bee colony [29], Particle swarm optimization [30], Ant colony optimization [31, 32], Harmony search [33].

The group of self-scheduling techniques is base of minimization of the energy with taking in to account the coverage and connectivity [34, 35].

In [21] are compared all mentioned techniques for sensor deployment. The conclusion is that metaheuristic techniques have great performance for sensor deployment problem.

In this work, we apply ACO metaheuristic, as one of the best methods for solving combinatorial optimization problems. Our goal is to have the area under consideration fully covered with as few sensors as possible. A comparison is made with other methods solving the problem. Added to the algorithm is the possibility that there are obstacles impenetrable to the sensor in the monitored area. Such an example is the surveillance of a store with cameras. There may be columns or billboards that reduce the visibility of the cameras. On the other hand, through the use of obstacles, spaces of arbitrary shape can be modeled.

2. Materials and methods

Sensor networks (wired and wireless), particularly cameras, take a large place in our everyday life. The reason for their increasing use is their ability to monitor large areas, respond in real time, and relatively simple to use. In civilian life, they are used to monitor sites such as train stations, airports, and large stores. When building a sensor network, the positioning of the sensors is of great importance. The coverage provided by the network as well as the number of sensors used are directly dependent on it. The economic cost of the network depends on.

2.1. Problem formulation

Each sensor (node) in the network monitors an area called a coverage area. A parameter called coverage radius Rcov determines the size of the sensor's observation and hence the monitored area. The coverage area is the area on the ground/floor that the sensor monitors. The goal is to place sensors, ensuring complete coverage of the assigned area. Positioning should be done to maintain full coverage of the area, using as few sensors as possible.

There may be opaque obstacles in the monitored areas. These can be columns, banners, elevator shafts, etc. These obstacles reduce the sensor coverage area to a distance less than the coverage radius. Thus, if a part of the monitored area remains uncovered, it is necessary to add sensors, i.e., obstacles must be taken into account.

2.2. Ant colony optimization

The idea for ant colony optimization comes from their way of searching for food. By using a chemical substance called a pheromone, when working in a group they can find the shortest path from the nest to the food source. This behavior is used to find the minimum of a function, with added constraints [36, 37]. The method uses probabilistic mechanism. The population statistics are kept and late is used for generation of new solutions. After that the new found solutions are used to calculate the probability in the next step.

A key point in the method is the representation of the problem through a graph. Solving it boils down to finding the shortest path in the graph under some constraints. Ants build solutions starting from a random node in the graph. They add subsequent nodes (solution elements) using a probability called the transition probability. The elements of the solution are marked with digital information corresponding to its importance. This is similar to pheromone in ants, shorter paths accumulate more pheromone and attract the next ants. The pheromone is initially set to the same value τ_0. Thus, before the exploration of the solution domain begins, all possibilities are equally likely.

The transition probability p_{ij}, to choose the node j when the current node is i, is based on the heuristic information η_{ij} and on the pheromone trail level τ_{ij} of the move, where $i, j=1, \dots, n$,

(1) $$p_{ij} = \frac{\tau_{ij}\eta_{ij}}{\sum_{k\in\text{allowed}} \tau_{ik}\eta_{ik}}.$$

When there are two or more nodes with equal probability, candidates for the next node in the partial solution, we choose one of them randomly.

Pheromone updating is carried out according to the next equation,

(2) $$\tau_{ij} \leftarrow \rho\tau_{ij} + \Delta\tau_{ij},$$

where $\Delta\tau_{ij} = 1/C(V)$, and $C(V)$ is the value of the objective function for the solution V.

When it is impossible to add new node in the current solution, the construction process stops.

2.3. Ant colony optimization for sensor deployment

The first component of ACO Algorithm is graph representation of the problem. Our problem graph is a rectangular grid. We will use two grids to solve the problem. The first will be with a small distance between the neighbor nodes. It will be used for coverage calculation and depends of application. For example, for cameras it is sufficient the distance between the nodes to be 10 cm and we will call it one unit.

The second grid will have larger distance between neighbor nodes. The nodes of the second grid are positioned on nodes of the first one. The distance between the nodes of the second grid depends to the coverage radius too. The second grid is used for sensor positioning. Using two grids reduces computation time because the ants only traverse the second grid, and it contains significantly fewer vertices, i.e., less candidates for inclusion in the solution.

The pheromone in this application is deposited on the nodes of the graph. Solution construction starts from random node of the graph. The ants include next node applying following heuristic information,

(3) $$\eta_{ij}(t) = s_{ij}\,(1 - b_{ij}),$$

where s_{ij} is the number of uncovered nodes, which the new sensor will cover, and b_{ij} is the solution matrix and the matrix element $b_{ij} = 1$ when there is sensor on this position otherwise $b_{ij} = 0$. When s_{ij} is larger, the new sensor covers more uncovered nodes, thus we expect that at the end less sensors will be used to cover all area. With the parameter $b_{ij} = 1$ we guarantee that maximum one sensor will be positioned on a node of the graph. The search process will stop when there is no more possibility to position new node, or when $p_{ij} = 0$. This means that there are no more vacant positions or that all space is already covered.

The initial pheromone τ_0 is a small positive number. Appropriate values are $\tau_0 = 0.5$ or $\tau_0 = 1/n_{\text{ants}}$, where n_{ants} is the number of used ants.

There are various variants of ACO methodology. The main difference is in the updating of the pheromone. In our algorithm we apply Max-Min Ant System (MMAS). In this variant of ACO, a lower limit $\tau_{\min}$ and upper limit $\tau_{\max}$ of the pheromone is introduced. When the pheromone value goes outside these limits, it is set equal to one of the limits, depending on which one it is closer to. In our algorithm, we used the asymptotic value of the pheromone as an upper bound $\tau_{\max}$, and as a lower bound we used $\tau_{\min} = 0.087\tau_{\max}$. We apply MMAS because is proven that it converge to the global optimum when the number of iterations converges to the infinity [38].

3. Results

Proposed ACO algorithm is adapted to optimally place sensors in a rectangular area in which there may be impenetrable rectangular obstacles or areas for which monitoring is not required. Examples of obstacles are columns, elevator shafts, kiosks, banners etc. Examples of areas where monitoring is not necessary are ticket offices, etc. The input data for the program are the dimensions of the area $N{\times}M$

(length and width), sensor coverage radius R_{cov}, number of obstacles, size of each obstacle (length and width) and the coordinates of its lower left corner. The lower left corner of the area has coordinates (0, 0) and the coordinates of the obstacles are calculated relative to it. On Fig. 1 is shown area where $M = 17$ and $N = 15$. There are two obstacles with coordinates of the lower left corners (3, 5) and (10, 0), respectively. With sizes (2, 4) and (4, 3), respectively.

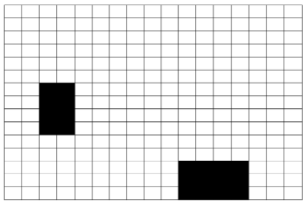

Fig. 1. Area with obstacles

The accuracy of the calculation depends on what size we want the unit of measurement to be. For example, for video surveillance, it is sufficient for the relative unit of measurement to be one decimeter (10 cm). Then, if the monitored area is 20 m×50 m, then 200 for length and 500 for width are given as input to the program. Coverage radius is also provided in a similar way. The dimensions of the obstacles are set in the same units of measurement as the dimensions of the area. The coordinates of the lower left corner of each obstacle are calculated based on its distance from the edges of the area in the corresponding unit of measurement, taking into account that the coordinates of the lower left corner of the area are (0, 0). When the sensors are cameras, the coverage radius is calculated from the height at which they are placed and the angle of view of the camera.

The proposed algorithm was tested for a square area with a side of 500 units and a coverage radius of 30 units. The algorithm is stochastic and therefore has been run 30 times. The test problem parameters are shown in Table 1.

Table 1. Test parameters

Parameter	Value
Area length	500
Area width	500
Rcov	30

A comparison with other sensor placement algorithms was made. It is also symmetrically placed on the sensors, where they are positioned at a distance from each other equal to the coverage radius Table 2. This guarantees complete coverage of the area, but we cannot guarantee that it will be fixed with the minimum number of sensors. Other three algorithms are based on genetic algorithm.

Table 2. Experimental results

Algorithm	Number of sensors
Symmetric	288
MOEA	260
NSGA-II	262
IBEAHD	265
ACO	232

The results for ACO in Table 2 are average and their range is in the interval [227, 239]. For other algorithms it is minimal number of sensors.

Using obstacles, we can apply the algorithm to areas other than rectangular ones. A U-shaped area can be depicted by adding an “obstacle” centered at the bottom of the area, see Fig. 2.

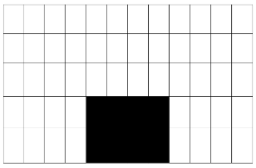

Fig. 2. U-shaped area

An S-shaped area is depicted with obstacles added to the left and right parts of the area as it is shown on Fig. 3

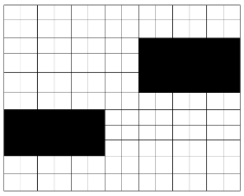

Fig. 3. S-shaped

A L-shaped area is depicted by adding an “obstacle” in one of the corners, Fig. 4.

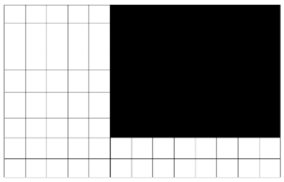

Fig. 4. L-shaped

An O-shaped area is depicted by adding an “obstacle” in the middle of the area Fig. 5.

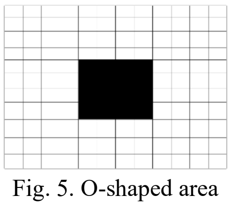

Fig. 5. O-shaped area

If there is an obstacle in the area that is not rectangular, then it is described by rectangles inscribed in it. Areas that have curves are described in a similar way. Then the area that is set as input is described rectangle encompassing all points of the actual area, and then with rectangles as obstacles the parts that do not belong to the actual area are described. On Fig. 6 is shown description of circular area, described approximately by inscribed rectangles.

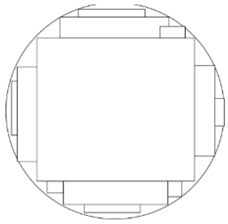

Fig. 6. Circular area

4. Discussion

Regarding the achieved results, we observe that proposed ACO algorithm cover hall area with less sensors than other algorithms. This means that our algorithm performs better, in more optimal way than others. More over the proposed algorithm and developed on its basis software, take in to account different obstacles. The idea of obstacles is used to approximately represent various kind of shapes. On a Figs. 1-5 is shown how to represent U-shaped area, S-shaped area, L-shaped area and O-shaped area. On a Fig. 6 is shown an example how to approximate circular area. In a similar way any kind of not rectangular shape can be represented and after, our algorithm can be applied and position sensors in an optimal way.

5. Conclusion

In this paper we propose metaheuristic algorithm, based on ACO, for optimal monitoring an area. The area can have any shape and described approximately by inscribed rectangles. The algorithm takes in to account opaque obstacles, when calculates covered by sensors area. Comparison with other methods show that our ACO algorithm uses less sensors for monitoring the same area. More over our algorithm is faster. It finds reported results for one-hour running. The other methods need 10 hours on a similar computer. As a future work, we will develop hybrid algorithms including a local search procedure to improve found solutions.

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