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Ant Colony based Coverage Optimization in Wireless Sensor Networks

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***Abstract*— Maximizing the covered area of wireless sensor networks while keeping the connectivity between the nodes is one of the challenging tasks in wireless sensor networks deployment. In this paper, we propose an ant colony-based method for the problem of sensor nodes deployment to maximize the coverage area. We model sensor locations as a graph and use an adapted ant colony optimization-based method to find the best places for each sensor node. To keep the connectivity of the sensor network, every sensor must be covered by the other sensors; this is a hard constraint that is applied to the cost function as a penalty. The proposed algorithm is evaluated with different numbers of sensor nodes and sensing ranges. The simulation results showed that increasing the number of iterations in the algorithm generates a better coverage ratio with the same number of nodes.**

***Index Terms*—Wireless sensor networks, node deployment, coverage maximization, ant colony optimization.**

I. Introduction

In RECENT years, the new generation of smart buildings, structures, vehicles, and factories are widely dependent on proper sensing and collecting of data from the environment. Wireless Sensor Networks (WSNs) are one the technologies that can be used to collect different kinds of information from various environments including harsh areas such as seabed, mountains, or urban areas [1]. Technically, a WSN is a set of small, low-energy sensor devices that can connect to the other nodes over wireless communication platforms. These devices may have different types of hardware and software capabilities such as processing units, sensing modules, and memories. Recent advances in electronic and hardware technologies allow the generation of a wide range of tiny, low-cost, low-energy devices that support local processing, sensing, and various communication methods. The diversity and capabilities of these devices grow exponentially which allows us to use them in different application areas. For example, collecting the status of patients and health care devices in hospitals, automation of activities and increasing the quality and efficiency of products in agriculture, monitoring the status and condition of devices in a factory, controlling the objects in smart homes, developing efficient rescue systems, real-time monitoring systems of critical infrastructures, and providing ad-hoc or mobile communication platforms are some applications of WSNs.

Maximizing the coverage area of WSNs and keeping the connectivity between the nodes are two essential necessities in these networks. Ideally, WSN should cover the maximum possible area and all available devices in the network should be able to communicate with other nodes. Generally, these two-requirement conflict with each other. Increasing the coverage area of a WSN needs to increase the distance between deployed nodes which weakens the connectivity. Placing the nodes far from each other reduces the possible alternate paths between the nodes and also weakens the strength of the wireless signals which may affect the connectivity between the nodes. To increase the connectivity robustness, we need to deploy more dense networks which allows to create alternative communication paths between the nodes. However, dense networks usually cover a limited area which is not acceptable in most applications. Some studies propose predefined deploying patterns that optimize both connectivity and coverage but most of the times placing the sensor nodes in the desired locations is not possible. Especially in harsh environments the nodes usually are distributed randomly which reduces the coverage area. In this paper, we propose an Ant Colony Optimization (ACO) based method to increase the coverage area of WSNs and preserve the connectivity between the nodes.

II. Related works

The importance of covering the maximum possible area in the region of interest has caused researchers to explore sensor deployment techniques to maximize the coverage in WSNs. The problem is considered in assorted conditions; some research projects take the communication or connectivity of the sensors into account while some do not, some papers try to find the minimum number of sensors while some take the number of sensors as a constraint and try to maximize the coverage for these sensors on the region of interest, some tries to cover just specified targets and some aim to cover the whole of the region of interest [2,3,4,5,6]. Various methods are used in this field but due to the good performance of the evolutionary algorithms in finding a solution for NP-hard optimization problems, these algorithms have been widely used to find the best deployment of nodes in order to maximize the coverage. Various swarm intelligence algorithms such as Genetic Algorithm and Particle Swarm Optimization algorithm are applied in literature [7,8,9,10,11].

Ant Colony Optimization algorithm is another evolutionary algorithm to solve the node deployment problem. In [12] an ACO based algorithm called ACO-Greedy is proposed to solve the Grid-based Coverage problem with Low-cost and Connectivity-guarantee (GCLC). The algorithm finds the minimum number of sensors with dynamic sensing and communication range that can provide full coverage, decrease deployment cost and prolong the lifetime of the network. [13] model the deployment problem as a multiple knapsack problem and use ant colony optimization algorithm to increase the coverage area. Network lifetime and coverage of the area are considered as objectives of the algorithm, which use the circle point concept. In [14] ACO-Discreet, a modification of Ant Colony Optimization is proposed which reduces the sensing cost with efficient deployment and enhanced connectivity. The algorithm includes two phases: at the first phase, the ordinary ACO is used for the grid-based problem coverage with low cost and connectivity-guarantee. At this level to focus on points far from the ant's current location, a heuristic value is used. After obtaining a solution at the first phase, at the second phase, ACO operates on the solution to remove redundant sensors.

The authors of [15] propose an algorithm called Optimized Strategy Coverage Control (OSCC) which aims to maximize the coverage of the region of interest in three steps. At the first step they establish a relation mapping model of the sensors based on geometric figure and prepare the network model, then uses ACO to enhance the coverage with the minimum number of sensors, reducing the energy spending of the whole network and optimizing the routing path. The algorithm benefits from node moving path and direction to find the optimal subset of iterative optimization. An improved ACO called EasiDesign is proposed in [16] to solve connectivity guaranteed point k-coverage problem. The aim is to find the best minimum subset of locations for sensors. For this purpose, every ant chooses a point from all points which sensors can cover the critical points, to do this, ants apply stochastic local decision and then the pheromone is updated based on the quality of the solution to help the algorithm to find better solutions in the next iterations. Obstacle avoidance and unavailable points are taken into account to increase the practicality of the algorithm.

III. Proposed Approach

Ant colony optimization algorithm is a probabilistic technique inspired by the behavior of real ants. The basic idea of this member of the swarm intelligence methods family is the way that ants find the best route to go from a point to a target point using pheromone (Fig.1). After modeling the search space of the problem and initializing parameters, the algorithm starts with a set of random solutions and improve them until satisfying a predetermined stopping condition. Ants choose their path to construct a solution based on a probability that depends on pheromone and heuristic. At the end of each iteration, when all of the ants represent a solution for the problem, the pheromone matrix is updated based on the quality of the solution, that is the corresponding cost. The best ant, which is the ant with the lowest cost (for minimization problem) among all ants is cached when an iteration ends and the final solution is the best of the bests. We use ACO to find the best locations in the region of interest to deploy the sensors to achieve maximum coverage.

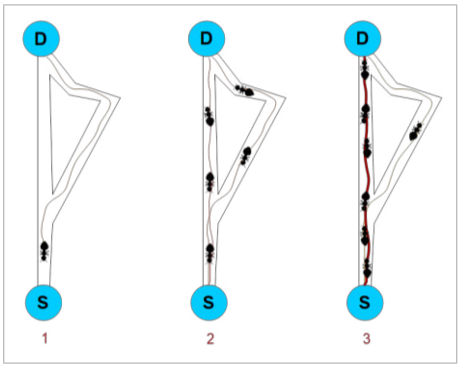


Fig. 1. Natural behavior of ants (Adapted from [17])

In order to formulate the problem, we assume the region of interest as a two-dimensional grid-based area. Sensors can locate at all points of the area. Each sensor can sense all points within its sensing radius and can communicate with all sensors within its communication radius. The purpose is to deploy the sensors so that they cover the maximum possible area in the region, considering each sensor must communicate with at least one other sensor. We denote the set of sensors with $S = \{s_1, s_2, \dots, s_n\}$ and location of sensor s_i and point p in the region of interest A is defined as (s_{i_x}, s_{i_y}) and (p_x, p_y) respectively. Euclidean distance between s_i and p is formulated as $d(s_i, p)$, shown in (1):

$$d(s_i, p) = \sqrt{(s_{i_x} - p_x)^2 + (s_{i_y} - p_y)^2} \tag{1}$$

If this Euclidean distance is equal to or lower than the sensing range r_s, the point can be sensed and is covered by the sensor si, otherwise, the point is not covered by s_i. This is the Boolean disk coverage model which is denoted as $c(s_i, p)$ in (2).

$$c(s_i, p) = \begin{cases} 1, & d(s_i, p) \le r_s \\ 0, & otherwise \end{cases} \tag{2}$$

So, the total covered points by the sensor s_i in area A is defined as (3). Considering $o(s_i, s_j)$ as the common points covered by s_i and s_j, the coverage function of the sensor set S on area A is shown in (4).

$$C(s_i, A) = \textstyle\sum_{\forall p \in A} c(s_i, p) \tag{3}$$

$$coverage(S, A) = \textstyle\sum_{i=1}^{n} C(s_i, A) - \sum_{i=1}^{n} \sum_{j=i+1}^{n} o(s_i, s_j) \tag{4}$$

We propose an ACO-based approach in which ants determine the coordinates of the sensors to deploy. For a $M \times M$ size area and n sensors, the solution space can be designed as a $(M \times M) \times n$ graph in which rows demonstrate all the possible coordinates that sensors can be placed, and each column represents one of the sensors. Fig. 2. shows the illustrated graph. An ant traverse on the graph and the path determines the coordinates of n sensors. For example, if the node on i'th row and j'th column of the graph is one of the nodes on the path of the ant, it means sensor number j must be located on the coordinate i. So, the path that every ant travels, can be shown as an $1 \times n$ array that each of its elements shows a location. Fig. 3. shows a sample ant path for 8 sensors problem in a 100×100 area. The first member 2580 means that the coordinates to locate sensor number 1 is (25,80), that is $(s_{1_x}, s_{1_y}) = (25{,}80)$.

All the original steps of ACO including creating the initial population and pheromone matrix, computing the probability matrix, pheromone updating and evaporation are the same in the proposed approach. To define the cost function of the algorithm, although the problem is maximizing the coverage, in order to include the communication condition, we reformulate the objective function as a minimization function. To do this, we use the total area of the region of interest, which means the area of the region of interest which is shown as *area(A)* is divided by the predefined function *coverage (S, A)*.

Each sensor must be covered by at least one other sensor, this is a hard constraint. We add this hard constraint as a penalty to the objective function. For each sensor s_i of the sensor set S, which is not covered by any other sensor, a penalty equal to $p(s_i)$ is considered, which is defined in (5). The communication range of all sensors is equivalent and is shown with r_c. Sensor s_i is covered by sensor s_j if the Euclidean distance between these two sensors is equal or less than r_c. If there is no sensor inside the communication range of the sensor s_i, it means the sensor is not covered by any other sensor and must suffer a penalty. In order to delete the impact of the number of the sensors, the normalized total penalty for sensor set S can be formulated as (6):

$$p(s_i) = \begin{cases} 0, & \exists s_j \in S: \ d(s_i, s_j) \le r_c \\ 1, & otherwise \end{cases} \tag{5}$$

$$P(S) = \frac{\sum_{i=1}^{n} p(s_i)}{n} \tag{6}$$

In order to intensify the effect of the penalty on the objective function, we use κ as the coefficient of the penalty

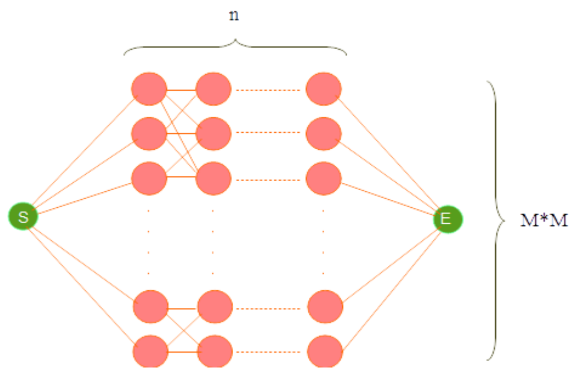


Fig. 2. Graph model of the proposed approach

S1	S2	S3	S4	S5	S6	S7	S8
2580	0265	1152	9804	7204	3288	1425	6206

Fig. 3. A sample ant path

which is a very large number. The final objective function of the proposed ACO algorithm is called *F(S)* and is shown in (7). The ant that has smaller *F* is the better ant and deposits more pheromone on the path.

$$F(S) = \left(\frac{area(A)}{coverage(S,A)}\right) + (\kappa \times P(S)) \tag{7}$$

All the ants travel based on the pheromone matrix and construct new paths and solutions. The algorithm continues until the stopping condition is satisfied, which is iteration in our case. At the end, the ant with the least cost that is maximum coverage and penalty equal to zero is the best ant which gives the best coordinates for n sensor on area A to be placed and have the most covered area.

IV. PERFORMANCE EVALUATION

To evaluate the performance of the algorithm, first we conduct experiments using various parameters in order to determine the optimum configuration of parameters for ACO-based deployment. We focus on the impact of ACO standard parameters as well as problem specialized parameters. The ACO parameters include the number of iterations, initial population size of ants, pheromone exponential weight, evaporation rate and parameters of the problem include sensing radius, number of sensors and penalty coefficient. The algorithm is implemented using MATLAB software with different values for the above parameters in a 100×100 grid-based sensing region, considering the maximum number of iterations as the stopping condition. Combinations of 50, 100, 200, 400, 500 and 1000 iterations with 20, 30, 40, 100, 200 population size, 10, 20, 50, 100 for penalty coefficient and 0.3, 0.5 evaporation rate are tested and the determined optimal parameters which have caused better results are listed in Table 1.

After the creation of a random population of ants at the first iteration, in which each member demonstrates a random deployment of the sensors, the algorithm proceeds to improve the solution and find the optimal deployment. At every iteration, based on the information of the past iterations is reflected on the pheromone matrix, the algorithm finds a better solution. That is, we get better cost as we progress. This can obviously be seen in Fig. 4. which shows that the coverage rate improves in each iteration for the deployment problem of 32 sensors with a sensing radius set to 10. It should be mentioned that considering the communication between sensors as a hard constraint and injecting it to the cost with a high impact, leads ants to focus on finding solutions with the least penalty. The implementation results show that the algorithm finds solutions with penalty equal to zero at even early steps. As consequence the outcome of the algorithm is a deployment with high coverage rate and zero penalty, which means all sensors are in communication with at least one other sensor.

TABLE I. OPTIMAL PARAMETERS

Parameter	Value
Number of Iterations	200
Population Size	100
Evaporation Rate	0.05
Penalty Coefficient	10

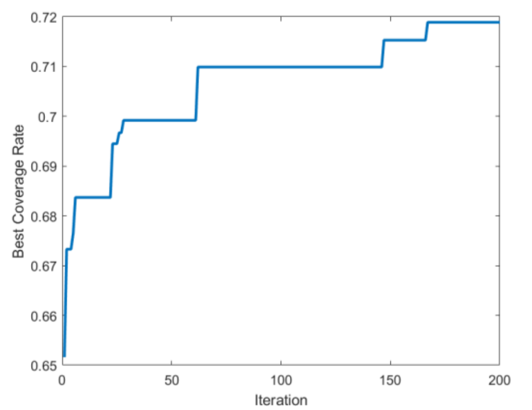


Fig. 4. Iterative process of the algorithm optimization

To evaluate the impact of the sensing range on coverage rate, we simulated the algorithm with three different sensing ranges: 5, 10 and 15 meters. We assume that all the sensors have the same sensing range and the communication range of the sensors is twice the sensing range. The algorithm tries to

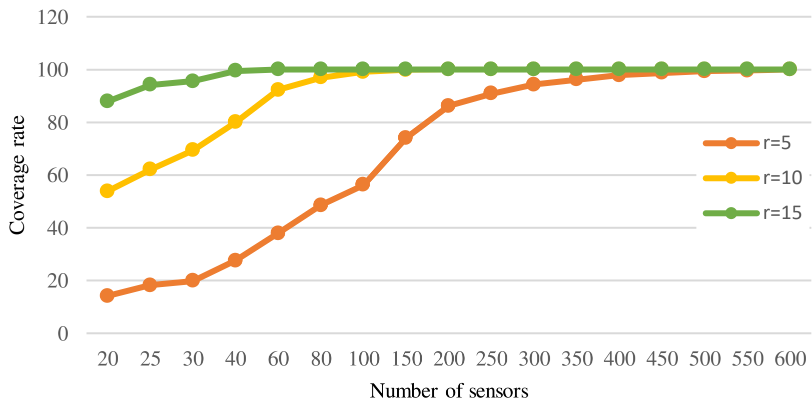


Fig. 5. Iterative process of the algorithm optimization

find the best coordinates to locate the sensors with the predetermined sensing range, such that they cover the maximum area, ensuring that every sensor is in the communication range of at least one other sensor.

One another determinative parameter in coverage rate is the number of sensors. As the region of interest gets larger more sensors are needed for full coverage of the area but not all time full coverage is the aim. Determining the number of sensors can be considered as the result of a trade-off between the cost of supply and maintenance and desired coverage rate.

To evaluate the impact of the number of sensors we simulated the algorithm with 18 different numbers in the range of [20 600]. In order to present the combinational effect of sensing range and number of sensors, we illustrated how coverage rate changes for different sensing ranges and number of sensors in Fig. 5. It can be seen that the coverage rate increases when the number of sensors becomes more. The sensing range has similar and even more effect, the larger

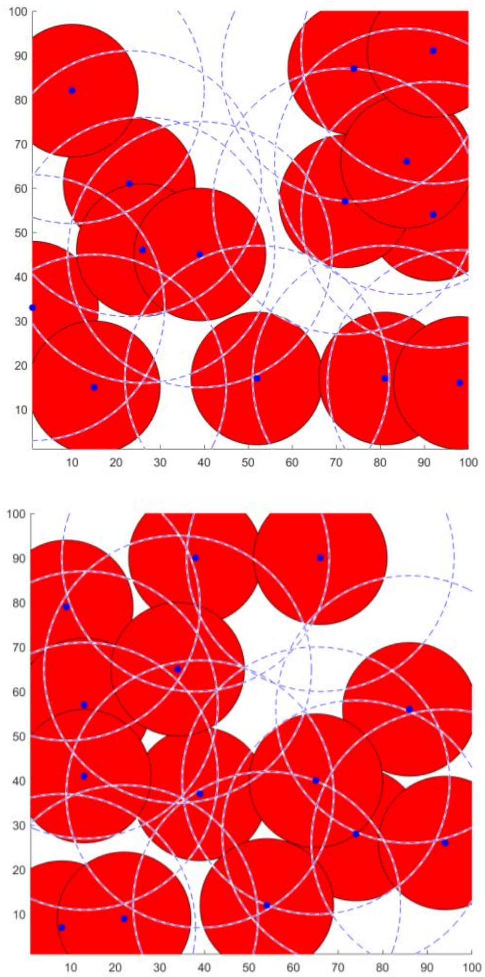


Fig. 6. Sensor Deployment of $n = 14$, $r_s = 15$ before(top) and after(bottom) optimization

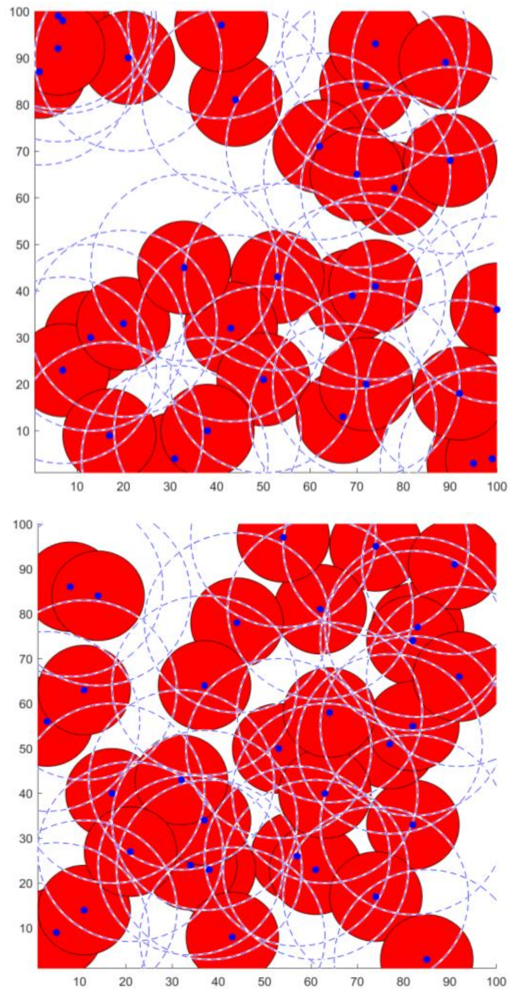
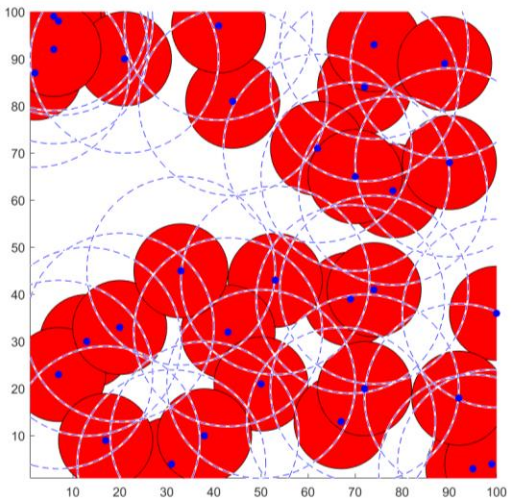


Fig. 7. Sensor Deployment of $n = 32$, $r_s = 10$ before(top) and after(bottom) optimization

range the more coverage rate. And obviously larger sensing range results in more coverage with fewer sensors compared to sensors with smaller range.

The algorithm processes on a random deployment and improves it to an approximate optimal solution. To compare the first situation of the sensors with the situation of the sensors which are located in the coordinates determined by the proposed algorithm, Fig. 6, Fig.7 and Fig. 8 show the region of interest covered by sensors before and after optimization for the number of sensors which have about 100% maximum possible coverage rate. The coverage rate of 14 sensors with a sensing range 15 m is 76.1% for 32 sensors with $r_s = 10$ m the rate is 72.6% and 128 sensors with a range of 5 m cover 67.3%, of the region of interest. As shown in the figures, all the deployments resulted from the algorithm ensuring the communication condition and all of the sensors are in communication with at least one other sensor.



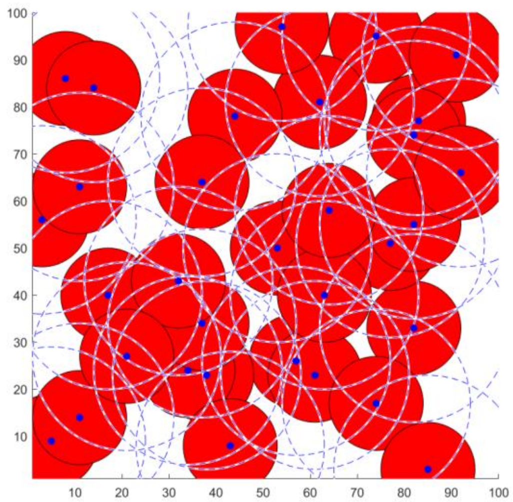


Fig. 8. Sensor Deployment of $n = 128$, $r_s = 5$ before(top) and after(bottom) optimization

CONCLUSION

In this work, we consider the problem of sensor nodes deployment to maximize the coverage area. We model sensor locations as a graph and use ACO to find the best places. Every sensor must be covered by other sensors; this is a hard constraint that is applied to the cost function as a penalty. The algorithm is evaluated with different numbers of sensors and sensing ranges. Better locations are found and the coverage rate increases as the algorithm iterates. Simulation results showed that our proposed sensor deployment approach improves the coverage rate of a set of sensors that are deployed randomly by finding new places to deploy. The simulation results showed that the prosed algorithm can increase the coverage ratio of the network to 76.1% with 14 sensor nodes where the sensing range of each node is 15 m. As future work, the proposed algorithm will be evaluated in a real testbed environment.

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