EasiDesign: an Improved Ant Colony Algorithm for Sensor Deployment in Real Sensor Network System

Dong Li\textsuperscript{1}, Wei Liu\textsuperscript{1,2}, Li Cui\textsuperscript{1}
\textsuperscript{1}Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China 100190
\textsuperscript{2}Graduate School of Chinese Academy of Sciences, Beijing, China 100190
E-mail: {lidong, liuwei_76, lcui}@ict.ac.cn

Abstract – In this paper, we formulate coverage requirements of the sensor network as a minimum-cost connectivity guaranteed point $k$-coverage problem. An improved ant colony algorithm (EasiDesign) is proposed to achieve the approximate solution to this optimization problem. We made modifications in the convergence strategy and the ant state transition rule of the general ant colony optimization. Considering the practicability issues, we design the obstacle avoidance and the routing cost tradeoff strategies to ensure that EasiDesign can work efficiently. The simulation results show that EasiDesign uses less sensor nodes than the existing works in the same scenario. The performance is also demonstrated through a real sensor network system for the environment monitoring in the Forbidden City.

I. INTRODUCTION

Many civil applications of sensor network require a connected network that can cover the sensing field with predefined redundancy and meanwhile the system cost should be minimized. Thus, the minimum-cost $k$-coverage problem has become one of the fundamental but challenging research issues in sensor networks. There are several challenges in resolving this problem. Firstly, it is hard to design an approximate algorithm which can get high quality solutions in both system cost and routing cost. Secondly, The proposed algorithm should have the ability to avoid obstacles. Finally, The scalability of deployment algorithm should be considered.

Regarding these challenges, research efforts have been made in three categories: (i) In theoretical analysis [1, 2], constructing a network to $k$-cover critical grids/points with minimum sensors has been proved to be NP-Complete. (ii) In the design of approximate algorithm [3-5], the $k$-coverage and other constraints, such as the connectivity of network, the density and the number of sensors, are combined in various ways to form optimization problems. (iii) In design of network protocols [6-8], the coverage is a key metric which is jointly considered with the degree of connectivity [6], the cluster size [7] and the energy efficiency [8].

However, most of the existing literatures do not consider the system cost and the routing cost in the meantime, but the routing cost has a serious effect on the lifetime and the data loss rate of system. End users care about these metrics as well as the system cost. In addition, the obstacle avoidance is rarely mentioned in previous works. Therefore, the practicability of these studies is questionable. In this paper, we focus on the practical lightweight deployment algorithm design for the real system. The proposed algorithm is finally validated in the commercial sensor network system for the relic protection in the Forbidden City.

We first formulate the deployment requirements in real system as the minimum-cost connectivity guaranteed point $k$-coverage problem (MCGP $k$-coverage problem). An improved ant colony algorithm (EasiDesign) for sensor deployment is proposed to solve this problem. We make several modifications in the traditional ant colony optimization (ACO) to help ants work efficiently in the next point selection process. We discuss the practicability in two aspects: (i) the tradeoff between the number of sensors and the routing hops, and (ii) the method to avoid obstacles. The simulation results and the real system validation both demonstrate the effectiveness and practicality of the proposed approach.

The remainder of this paper is organized as follows. In Section II, we formulate the problem. Section III describes the detailed design. Section IV discusses the practicability issues. We present the simulation results in Section V and the real system demonstration is shown in Section VI. We conclude in Section VII.

II. PROBLEM FORMULATION

We regard the sensing field as a region comprising discrete points on which sensor nodes can be placed. The sensing field is defined as a connected undirected graph $G = (V, E)$, where $V$ is the set of candidate points for placement and $E$ is the set of links $(u, v)$, where $u, v \in V$. Let $d(u, v)$ be the distance between neighboring point $u$ and $v$. $r_c$ is the communication radius of sensor nodes. The set of critical points which should be covered by sensors is denoted as $C$ and $C$ is assumed to be the subset of $V$.

We employ the binary sensor model where a sensor can detect the event within the sensing radius $r_c$. Let $R_v$ be the set of candidate points which are in the sensing region of point $v$. Let $\xi_c, c \in C, v \in V$ be a Boolean variable. If $c \in R_v$, $\xi_c = 1$, otherwise $\xi_c = 0$.

The MCGP $k$-coverage problem is to find a set $P$ of candidate points to place sensors so that every critical point is covered by at least $k$ sensors and the number of sensors is minimized. Moreover, given the position of sink node $t$, every point $v \in P$ should have a simple path $p_{sv}$ to the sink. This problem can be restricted to the critical-grid coverage problem that has been proved to be NP-Complete [1].
III. THE DEPLOYMENT ALGORITHM

A. Basic Idea

In this section, we present the deployment algorithm (EasiDesign) to construct approximate solution for the minimum-cost connectivity guaranteed point k-coverage problem. The basic idea of EasiDesign is to let the ant move and place sensor nodes on the candidate points in the sensing field. At each construction step it moves along the path leading to the points where a sensor can cover the critical points. The ant probabilistically chooses a point by the pheromone value on the link from the current point to the candidate. Once each ant has constructed a solution, the solution with minimum number of sensors is cached. The whole procedure is repeated until the maximum number of iteration is reached and then the best solution is selected. We give pseudo code in Algorithm 1.

The input parameters include: \( k \), the least covered times of a critical point; \( c_{\text{cut}} \), the number of ants; \( i_{\text{max}} \), the maximum number of iterations and \( n_t \), the period to run the pheromone constraining process which is explained in Section III-C.

Algorithm 1: Deployment Algorithm (EasiDesign)

1: EasiDesign( \( k \), \( c_{\text{cut}} \), \( i_{\text{max}} \), \( n_t \) )
2: randomly select the start points for all the ants;
3: \( i = 0 \); // the counter of iterations;
4: \( \text{WHILE} \ (i \leq i_{\text{max}}) \ \text{DO} \)
5: \( \text{REPEAT} \)
6: \( \text{FOR} \ j=0 \text{ to } j=c_{\text{cut}} \ \text{DO} \)
7: SelectNextPoint();
8: \( \text{// each ant probabilistically chooses the next point} \)
9: \( \text{ENDFOR} ; \)
10: \( \text{UNTIL} \) all the ants have constructed their solutions;
11: compute the min-cost solution and insert it into set \( P \);
12: GlobalPheromoneUpdate();
13: \( \text{IF} \ (i/n_t == 0) \ \text{THEN} \)
14: PheromoneConstraining();
15: \( \text{ENDIF} \)
16: \( i=i+1 \);
17: \( \text{ENDWHILE} \)
18: select the best solution in set \( P \);
19: RETURN the best solution;

In Algorithm 1, we have three critical algorithmic components: (i) In line 7, function SelectNextPoint() is to probabilistically select the next point; (ii) in line 12, function GlobalPheromoneUpdate() is to provide general pheromone value updating process when all the ants have constructed their solutions; and (iii) in line 14, function PheromoneConstraining() is to adjust the pheromone value to avoid the premature convergence. We design new strategies for these three critical components to improve the applicability of the proposed algorithm in the large network.

B. Next Point Selection

The next point selection process has two steps: Firstly, an ant identifies the candidate collection points for the next stop; secondly, the ant applies a stochastic local decision policy to select a point in the candidate collection. In this subsection, we explain the strategy used in these two steps.

All the points in the communication range of current point are candidates. In large scale application, the selection procedure becomes more stochastic which leads to low quality solution and long convergence time. To improve performance, we use a greedy strategy to reduce the amount of candidates. The point where a sensor can reach the uncovered critical points should be considered at first by the ants. We formulate the strategy as following:

\[
N^*_{i} = \begin{cases} 
N_{\text{dp}}^*, & \text{if } N_{\text{dp}}^* \neq \emptyset \\
N_{\text{ul}}^*, & \text{if } N_{\text{ul}}^* \neq \emptyset 
\end{cases}
\]

Where \( N^*_{i} \) is the set of candidate next points when \( i-th \) ant stands on point \( v \) and set \( N^*_{\text{dp}} \) contains all the points whose distance to point \( v \) is less than the communication range of the sensor. \( N^*_{\text{ul}} \) is the subset of set \( N^*_{\text{dp}} \) and contains the points on which the sensor could cover at least one uncovered critical point. The choosing probability of point \( u \) for the \( i-th \) ant is:

\[
p^{i}_{vw} = \sum_{m \in C_{\nu}} \eta^{i}_{m,v} \bigg/ \sum_{m \in C_{\nu}} \eta^{i}_{m,v}, \quad u \in N^*_{i}
\]

Where \( \tau^{i}_{vw} \) is the pheromone value of \( u \); \( \alpha \) is the parameter to control the influence of \( \tau^{i}_{vw} \); \( \beta \) is the parameter to control the influence of \( \eta^{i}_{m,v} \); \( \eta^{i}_{m,v} \) is the desirability of link(v,u) from the perspective of the \( i-th \) ant and the definition is:

\[
\eta^{i}_{m,v} = \sum_{m \in C_{\nu}} \tau^{i}_{m,u} + 1
\]

Where \( C_{\nu} \) is the set of critical points which can be covered by sensors on point \( u \), and \( r^{i}_{m} \) is the uncovered times of critical point \( m \). \( \eta^{i}_{m,v} \) indicates the potential capability of a point to cover more critical points. In Fig1, the \( i-th \) ant is standing on point \( v \) and computing the selection probability of point \( u \) which has two neighboring critical point \( c_1 \) and \( c_2 \). \( c_1 \) has been covered by the sensor on point \( v \). To build a 2-coverage deployment, \( c_1 \) has to be covered by at least another sensor, which is denoted as \( r^{i}_{c_1} = 1 \). Meanwhile, \( c_2 \) has not been covered, \( r^{i}_{c_2} = 2 \). If we choose \( u \) as the next point, we will satisfy the coverage requirement of two critical points. So the desirability of \( u \) is 4. To avoid the problem of dividing by zero, we set initial value as 1.

Fig. 1. An example of the uncovered times \( r^{i}_{m} \) and the desirability \( \eta^{i}_{m,v} \) of link(v,u).

C. Pheromone Update

After all the ants have constructed their solutions, the pheromone updating process is executed according to the quality of solutions generated. The updating rule in MAX-
MIN ant system (MMAS) [10] is applied. The pheromone value of $\text{link}(u,v)$ is performed as follows:

$$\tau_{u,v} = (1 - \rho) \tau_{u,v} + \Delta\tau_{u,v}^{\text{best}}$$ \hspace{1cm} (1)

Where $\rho$ is the pheromone evaporation coefficient which is experimentally set and $\Delta\tau_{u,v}^{\text{best}} = 1/L_{\text{best}}$ if point $u$ is used by the best solution in current iteration, otherwise $\Delta\tau_{u,v}^{\text{best}} = 0$, where $L_{\text{best}}$ is the number of sensors used in the best solution.

The pheromone constraining process is to constrain the pheromone value within the imposed limits, $\tau_{\text{min}} \leq \tau_{u,v} \leq \tau_{\text{max}}$. $\tau_{\text{min}}$ and $\tau_{\text{max}}$ are set by experience in MMAS algorithm, which is complex to control and probably leads to stagnation or premature convergence.

Facing these drawbacks, we first give a configuring rule for $\tau_{\text{max}}$ as follows:

$$\tau_{\text{max}} = \frac{1}{\rho L_{\text{best}}}$$ \hspace{1cm} (2)

Equation (2) guarantees a reasonable convergence time. Big decay coefficient will lead to premature convergence, but meanwhile the maximum value of pheromone becomes smaller, which will encourage ants to choose more points and hence produce more different solutions. When $\rho$ becomes smaller, more pheromone will be left on the links used by the best solution, which leads to a quick convergence.

To get a simple control mechanism, we propose an individual period for the constraining process of $\tau_{u,v}$. This period is counted in the number of iteration, denoted as $n_{\text{en}}$. Thus, we have a method to indirectly control the updating speed of $\tau_{u,v}$, which is more effective than changing $\tau_{\text{min}}$ in forms of real number.

IV. PRACTICABILITY ISSUES

A. Routing Optimization

Without the routing consideration, the algorithm often results in unpractical solutions as shown in Fig.2(a), where all the points should be 1-covered. This solution has 32 sensors but the total length of routes from sensors to the sink is 202 hops. Some sensors have obviously unreasonable routing paths to the sink like the one on point $v$. In real system, the solution with high routing cost has a serious negative effect on the network lifetime, data loss rate and packet delivery delay. In this section, we take the routing cost into consideration by means of modifying the pheromone updating rule in equation (1), denoted as follows:

$$\Delta\tau_{u,v}^{\text{best}} = \begin{cases} \frac{1}{L_{\text{best}} H_{\text{best}}^u}, & \text{u is in best solution;} \\ 0, & \text{otherwise} \end{cases}$$ \hspace{1cm} (3)

Where $H_{\text{best}}^u$ is the hop count from $u$ to the sink in the current best solution. This rule makes it hard for the solution with high routing cost to attract other ants, which largely increase the algorithm practicability. The new result is shown in Fig.2(b).

In the large sensor networks, when we minimize the number of hops, the transiting traffic among the nodes increases. Consequently the energy consumed increase and the first sensors that fall are near the base station [11]. Considering this situation, we add a special function at the end of EasiDesign to increase the number of sensors within two hops to the sink. The deployment policy is to place backup node beside the sensors which is the cut point in the topology.

B. Obstacle Avoidance

In real system, there are two kinds of obstacle: the physical obstacle like the trees, and the unavailable positions to place sensors. In this section, we improve EasiDesign to avoid obstacles. We add the shielding line and the unavailable point into the definition of the sensing field, as shown in Fig. 3. The shielding line is a vertical or horizontal line that can locate anywhere in the sensing field. If the line between two points has an intersection point with the shielding line, these two points can not communicate with each other. An ant can not place sensors on the unavailable points. With the advantage in path finding of ACO algorithm, we add an obstacle detection method in next point selection process to guide ants to go around. For example, in Fig.3, the ant locates on point $v$. A shielding line stands between $v$ and $n_2$, so $n_2$ is deleted from the candidate set.

V. PERFORMANCE EVALUATION

To evaluate the performance and determine the optimum configuration of parameters for EasiDesign, we focus on the following aspects: (i) the impact of $\alpha$ and $\beta$ in SectionIII.B; (ii) the impact of pheromone constraining process and the setting of constraining period $n_{\text{en}}$; (iii) the impact of routing optimization component in EasiDesign. In simulations, we set the pheromone evaporation parameter $\rho = 0.5$ and use 30 ants.
The sensing radius and communication radius of a sensor is respectively configured as 180m and 90m for indoor scenarios. The distance between two neighboring points is less than 90m. All the candidate points in the sensing field are set to be critical points. The coverage requirement is set to be 1.

Parameter $\alpha$ and $\beta$ are important influence factors in the next point selection rules. The purpose of our experiments is to find the optimum combination settings of $\alpha$ and $\beta$. We run the simulations in three difference scales of sensing field (7*7, 11*11 and 13*13 points) with the constraining process running period $n_e = 30$, as shown in Fig.4. The result shows that the optimum combination of $\alpha$ and $\beta$ is (2, 4) or (2, 3), which is also proved in other works [9, 12]. In following experiments, $\alpha$ and $\beta$ is set to be (2, 3).

4. The constraining process of pheromone in EasiDesign makes the quality of the solution change in a wave pattern, which has higher probability to get better result, while the MMAS tends to quickly converge to a steady result.

To evaluate the impact of the pheromone constraining process, we compare EasiDesign and the MMAS algorithm in the sensing field of moderate scale (13*13 points). The changing of the best solution iteration process is shown in Fig.4. The constraining process of pheromone in EasiDesign makes the quality of the solution change in a wave pattern, which has higher probability to get better result, while the MMAS tends to quickly converge to a steady result.

![Fig. 4. The changing of the best solution in the runtime of EasiDesign using pheromone constraining process (vs. MMAS)](image)

To evaluate the impact of the running period $n_e$ of pheromone constraining process, we simulate EasiDesign in four different scales with 49, 81, 169 and 225 points. $n_e$ is increased from 5 to 30. Fig. 5 shows that the number of sensors increases slowly when $n_e$ becomes big in small scales, while the number decreases in large scales. The reason is that the local optimum solution is probably the global best solution in small scale scenario (sensing field with 49 and 81 points). The short constraining period can react quickly to the temporal best solution. However, this situation changes when the scale of sensing field grows. In large scale scenario, the local optimum solution is often not the best one in the global view. The short constraining period probably guides the ants to a wrong direction.

![Fig. 5. The impact of running period $n_e$ of pheromone constraining process in varying scale sensing field](image)

To evaluate the impact of the routing optimization component, we compare the resolutions computed by EasiDesign with and without routing optimization. The result is shown in Table I. An important improvement is achieved in the total routing hops with the cost of a small number of redundant sensors. This benefit decreases when the scale of sensing field grows, because the modified pheromone updating rule in equation (3) also tends to go after the temporal optimum solutions.
TABLE I
THE IMPACT OF ROUTING OPTIMIZATION IN EASIDESIGN

<table>
<thead>
<tr>
<th>Scale</th>
<th>Sensors</th>
<th>Hops</th>
<th>Sensors</th>
<th>Hops</th>
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</thead>
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<td>5x5</td>
<td>6</td>
<td>26</td>
<td>7</td>
<td>16</td>
</tr>
<tr>
<td>9x9</td>
<td>21</td>
<td>79</td>
<td>23</td>
<td>40</td>
</tr>
<tr>
<td>15x15</td>
<td>57</td>
<td>554</td>
<td>61</td>
<td>323</td>
</tr>
<tr>
<td>19x19</td>
<td>106</td>
<td>1188</td>
<td>115</td>
<td>895</td>
</tr>
</tbody>
</table>

VI. REAL SYSTEM DEPLOYMENT

To demonstrate the efficiency of EasiDesign in real system, we use EasiDesign to compute the placement plan in the wireless sensor system for relic protection in the Forbidden City. The sensors are placed in the cabinets which are used for the exhibitions and normal preservations. The temperature, humidity and the intensity of illumination are monitored periodically. The system generates alarms when the abnormal event is captured. This system has served for more than ten international exhibitions since July 2007. The devices and photos of different real monitoring scenarios in the palaces of Forbidden City are shown in Fig. 6.

Fig. 6. The sensor node, sink used in the Forbidden City and the display of a node in a sealed cabinet during exhibition.

In the early time, manual deployment led to unsatisfying system cost and link qualities. EasiDesign achieved a better placement plan. Figure 8 shows a real example. In Wumen Palace, sealed cabinets and thick walls are configured as the physical obstacles. In the cabinet, the sensors are required to be invisible to the tourist so that positions near the relics are configured as the unavailable points. With 33 critical points, EasiDesign used 34 sensors while the previous manual deployment used 41 sensors. The data loss rate was also reduced from 8% to 1% due to the connectivity guaranteed routing consideration. The 2-coverage topology generated by EasiDesign is shown in Fig. 7.

Fig. 7. Deployment solution in Wumen Palace of Forbidden City.

VII. CONCLUSIONS

In this paper, we studied the minimum-cost CGP k-coverage problem in real sensor network system. We design an approximate algorithm (EasiDesign) based on the ant colony optimization. We made modifications in the next point selection process and the pheromone updating process according to the characteristics of sensor network. We focus on two kinds of practical problems: optimizing the routing hops and avoiding obstacles. We first give a new pheromone updating rule which considers not only the number of sensors but also the routing cost in the constructed solution, and then we design an obstacle detection component to guide the ants to go around the obstacles. In the simulations, we discuss the optimum configuration of key parameters in EasiDesign and prove EasiDesign achieves better performance than the traditional ant colony algorithm. With routing optimization method, EasiDesign largely reduces system routing cost by a small number of redundant sensors. We used EasiDesign in the real sensor network system for the relic protection in the Forbidden City. The results indicate that EasiDesign can work efficiently in complex real scenario.

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REFERENCE