WIRELESS SENSOR NETWORK ENERGY EFFICIENT COVERAGE METHOD BASED ON INTELLIGENT OPTIMIZATION ALGORITHM

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ABSTRACT. As a basic and fundamental problem in wireless sensor network (WSN), the network coverage greatly reflects the performance of information transmission in WSN. In order to achieve a good balance between target coverage and energy consumption, in this paper, we propose a novel wireless sensor network energy efficient coverage method based on genetic algorithm. Particularly, the goal of this work is to cover a 2D sensing area via selecting a minimum number of sensors. Moreover, the deployed wireless sensors should be connected to let each sensor be connected a path to the base station. Afterwards, genetic algorithm is used to compute the minimum number of potential positions to let all targets be k-covered and all sensor nodes be m-connected, and each chromosome is set to be the number of potential positions. Finally, we provide a simulation to test the performance of the proposed method, and simulation results demonstrate that the proposed method can achieve high degree of target coverage without wasting extra energy.

1. Introduction. The wireless sensor network (WSN) is designed to achieve the perception, processing and transmission of information, and WSN is developed based on modern information technology, computer technology and communication technology [7, 28]. Moreover, WSN refers to a wireless communication network in which the wireless communication module is exploited to the sensor node, and it is made up of a great number of sensor nodes with self-organization and multi-hop information packet transmission [3, 1]. For a given sensing area, each sensor is responsible to collect information to users via perception, acquisition, processing and transmission of information [4]. Furthermore, WSN has been widely used in

2010 Mathematics Subject Classification. Primary: 58F15, 58F17; Secondary: 53C35.
Key words and phrases. Wireless sensor network, energy efficient coverage, intelligent optimization algorithm, genetic algorithm, fitness function.

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many areas, such as modern agriculture, national security, national defense security, environment monitoring, health care, and so on [26, 23].

Coverage problem refers to a basic problem in WSN. When constructing the WSN, a set of wireless sensors are allocated in a specific region [20]. Each active sensor is able to detect objects in its sensing range, which is a particular region centered at the location of the sensor. Hence, we define an object in the region of interest is covered, only if this region is covered by at least one sensor in WSN [19, 16]. Each node in the WSN has a limited sensing range and a limited communication range. The sensing coverage of a sensor node refers to the area determined by the sensing range of the sensor node. Sensing coverage of WSN means the collective coverage of the WSN’s sensor nodes [11]. In addition, sensor nodes in WSN have low power energy supply and they are difficult to be charged [10, 6]. Therefore, how to effectively save energy consumption in WSN is of great importance. On the other hand, the network coverage control should balance and reduce the energy consumption with ensuring the network coverage quality at the same time [2].

In this paper, we regard the WSN coverage problem as an optimization problem, and solve it by the genetic algorithm. The paper is organized as follows. In the next section, we propose the related works about coverage problem in WSN. In section 3, we formulate the issue of target coverage in WSN. Afterwards, we propose a novel Wireless sensor network energy efficient coverage method based on genetic algorithm in section 4. Section 5 conducts an experiment to validate the effectiveness of the proposed method. At last, this paper is concluded in section 6.

2. Related works. Coverage problem refers to a node placement optimization problem in the coverage configuration before wireless sensors deployment, and the objective is to seek the optimal locations to install sensor nodes. Target coverage is one of the most important issues in wireless sensor networks, and efficient target coverage algorithm can promote the performance of wireless sensor networks. In this section, we will discuss the existing works about target coverage problem in wireless sensor networks.

Yang et al. aimed to determine the locations to place the minimal number of nodes used for sensing and relaying such that deployed nodes 1) cover all targets, 2) have a path to the sink, and 3) have energy neutral operation. In this work, the authors convert the MEHNP-ENCC as a mixed integer linear program, and then propose an MILP-based method [27].

Wang et al. proposed a partial coverage method, and a near perfect coverage rate is obtained by least nodes to save the energy of the WSN system. The proposed approach is able to adjust required coverage rate to obtain degradation in terms of the number of active sensor nodes, and then constructs a multi-hop cluster network [24].

Sun et al. proposed a new algorithm with multi-objective optimization of coverage to enhance node coverage. This works provided the proportional relationship of the energy conversion function between the working node and its neighbors, and then exploited this relationship in scheduling low energy mobile nodes. Finally, the proposed method can achieve energy balance [22].

Pananjady et al. focused on the problem of energy efficiency in sensor networks, and aimed to solve the issue of maximizing the lifetime of coverage of targets in a wireless sensor network with battery-limited sensors. Extensive simulation experiments prove the effectiveness of the proposed algorithm [18].
Nguyen et al. proposed a cover set to seek the minimum set of sensors which can cover the sensing ranges within an interest area as a criterion for sensor activation. The aims of this work is to choose an optimal number of active sensors considering residual energy and the cover set and to keep live the sensors [17].

Han et al. analyzed main features of four recent energy-efficient coverage strategies via selecting four representative connected coverage algorithms, that is, 1) communication weighted greedy cover; 2) optimized connected coverage heuristic; 3) overlapped target and connected coverage; and 4) adjustable range set covers [13].

Boudali et al. proposed three efficient activities scheduling methods based on realistic sensor coverage models. The first one is centralized and it is based on a coverage graph. The second one is located and it ensures 1-barrier coverage. On the other hand, the third one is distributed and it can ensure 2-barrier coverage [9].

Alia et al. proposed a harmony search (HS)-based deployment algorithm which can locate the optimal number of sensor nodes, meanwhile it can maximize the network coverage and minimize the network cost. In this paper, the proposed method can combine the concept of adaptable length encoding in each solution vector to represent candidate sensor nodes [5].

Sun et al. proposed a coverage optimization algorithm in a complex dynamic environment, which can demonstrate the expectation and tolerance of sensor node coverage. According to the network energy, the communication path is optimized using a node status scheduling policy. Furthermore, the proposed method can achieve efficient match and constrains decay about sensor nodes energy [21].

Different from the above works, in this paper, we propose a novel method based on genetic algorithm to balance the trade-off between target coverage and energy consumption.

3. **Problem formulation.** In this work, we aim to cover a 2D sensing area by choosing a minimum number of sensors. The deployed sensors should be connected to ensure each deployed sensor is able to connect a path to the base station. Suppose that the sensing area is represented by a \( M \times N \) area. Particularly, a wireless sensor which is located at the \((i,j)\) position has the sensing range \( R_{\text{cov}} \) and the communication range \( R_{\text{com}} \). Based on \( R_{\text{cov}} \), the wireless sensor can cover the position \((k,t)\) in the area which satisfy the following condition:

\[
(i-k)^2 + (j-t)^2 \leq R_{\text{cov}}^2 \tag{1}
\]

Based on \( R_{\text{com}} \), the wireless sensor transmit data to its neighbor sensor in the position \((p,q)\) with the following condition satisfied.

\[
(i-p)^2 + (j-q)^2 \leq R_{\text{com}}^2 \tag{2}
\]

Particularly, in this work, we suppose that \( R_{\text{com}} \geq R_{\text{cov}} \). We assume that the sensing area is made up of \( N \) sensors \( S = \{s_1, s_2, \cdots, s_N\} \) with the size of \( m \times n \), and the sensing radius set is represented as \( R_S = \{R_{s1}, R_{s2}, \cdots, R_{sN}\} \), where \( R_{sN} \) is belonged to \([R_{s\text{min}}, R_{s\text{max}}]\).

For WSN, there are two primary types of coverage policy, that is, 1) binary model and 2) probabilistic model. The coverage of a WSN is estimated by computing the proportion to the number of targets which are covered. For the binary model, given a target \( T \) with the position \((x,y)\), the possibility which can be covered by sensor
s_i is calculated as follows.

\[
P(x, y, s_i) = \begin{cases} 
1, & \text{if } \exists i \in \{1, 2, \cdots, N\} \ d(s_i, T) \leq R_{Si} \\
0, & \text{otherwise}
\end{cases} \quad (3)
\]

On the other hand, the probabilistic model is able to deal with the uncertainty of sensor detection. The possibility that the target with the position \((x, y)\) can be covered by the sensor \(s_i\) is computed as follows.

\[
P(x, y, s_i) = \begin{cases} 
1, & \text{if } d(s_i, T) \leq R_{Si} - r_{ei} \\
0, & \text{if } d(s_i, T) \geq R_{Si} + r_{ei} \\
\exp\left(-\eta(r_{ei} - R_{Si} + d(s_i, T))^{\delta}\right), & \text{otherwise}
\end{cases} \quad (4)
\]

where \(d(s_i, T)\) is the distance between sensor \(s_i\) and target \(T\), and it is computed as follows.

\[
d(s_i, T) = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (5)
\]

Parameter \(\eta, \delta\) are used to estimate the detection probability.

\[
(r_{ei} - R_{Si} + d(s_i, T)) \quad (6)
\]

As the WSN is made up of \(N\) sensors, the probability that target \(T(x, y)\) is covered can be computed as follows.

\[
P(x, y, S) = 1 - \prod_{i=1}^{N} (1 - P(x, y, s_i)) \quad (7)
\]

Afterwards, the max value of coverage ratio is computed as follows.

\[
R_{m \text{cov}}(S) = \bigcup_{i=1}^{N} \pi \cdot R_{Si}^2 \quad (8)
\]

Considering the boundary effect of the sensing area, the coverage ratio is calculated as follows.

\[
R_{\text{cov}}(S) = \frac{1}{m \cdot n} \left( \sum_{x=1}^{m} \sum_{y=1}^{n} P(x, y, S) \ | \forall P(x, y, S) \geq \sigma \right) \quad (9)
\]

where \(\sigma\) refers to a threshold.

As shown in Fig. 1, we propose an example of node deployment scheme. The red color refers to the area being covered, and the white color means the area not being covered.

4. The proposed method. In this paper, we introduce the genetic algorithm to solve the WSN coverage problem, and genetic refers to a type of global optimization algorithm without carrying out sensitivity analysis [25, 15]. In the genetic algorithm, the optimal solution is done by the following steps: 1) selection, 2) crossover, 3) mutation and 4) survival of the fittest [14, 12].

The chromosome is represented by 1 and 0, and the number of each chromosome is set to the number of potential positions. Moreover, if the \(i^{th}\) gene is set to be 1, it means there is a sensor being placed at the \(i^{th}\) potential position, otherwise, this gene is set to be zero.

We aim to choose minimum number of potential position to let all target be k-covered and all sensor nodes be m-connected. The fitness function is constructed by the following parameters:

(1) Choosing the number of optimal potential position
Considering the boundary effect of the sensing area, the coverage ratio is calculated as follows.

\[
R_{\text{operator cov}}(S) = \frac{1}{m \cdot n} \left( \sum_{x=1}^{m} \sum_{y=1}^{n} P(x,y,S) \cdot \left| \forall \sigma \right| \right)
\]

(9)

where \(\sigma\) refers to a threshold.

As shown in Fig. 1, we propose an example of node deployment scheme. The red color refers to the area being covered, and the white color means the area not being covered.

**Figure 1.** An example of node deployment scheme

We suppose that there are \(M\) potential positions, among which there are \(K\) potential positions to be allocated sensors. Accordingly, this objective is defined as follow.

\[
O1 : \min (F_1) = \frac{M}{K}
\]

(10)

(2) Coverage degree

We define that \(Cov(\gamma_i)\) refers to the set of wireless sensors that are located in the sensing range of target \(\gamma_i\). Then, the coverage cost for target \(\gamma_i\) is defined as follows.

\[
CovC(\gamma_i) = \begin{cases} k, & \text{if } |Cov(\gamma_i)| \geq k \\ k - |Cov(\gamma_i)|, & \text{otherwise} \end{cases}
\]

(11)

Based on the above definition, this objective is illustrated as follows.

\[
O2 : \max (F_2) = \frac{1}{N \times K} \sum_{i=1}^{N} CovC(\gamma_i)
\]

(12)

(3) Connectivity degree

We define the sensors which are located in the range of sensor \(s_i\) as \(Com(s_i)\). Then, the connectivity cost for \(s_i\) is computed as follows.

\[
ConC(s_i) = \begin{cases} m, & \text{if } |Com(s_i)| \geq m \\ m - |Com(s_i)|, & \text{otherwise} \end{cases}
\]

(13)

Therefore, this objective is defined as follows.

\[
O3 : \max (F_3) = \frac{1}{M \times m} \sum_{i=1}^{M} ConC(s_i)
\]

(14)

Integrating all these three objectives, the multi-objective fitness function is defined as follows.

\[
Fitness = \chi_1 \cdot (1-F_1) + \chi_2 \cdot F_2 + \chi_3 \cdot F_3
\]

(15)
Overall objective: \( \max(Fitness) \)\)

Subject to \( \sum_{i=1}^{3} \chi_i = 1, \text{ and } \chi_i \in [0,1] \)\)

Due to the slow convergence speed of the genetic algorithm, we improve the standard genetic algorithm to balance the universality and effectiveness. The modification of genetic algorithm is listed as follows.

(1) Coding
We utilize the real numbers, to code the genetic algorithm, and \( n \)-D vector is regarded as individual. Individual is represented as \( X = (x_1, x_2, \cdots, x_n)^T \), where \( x_i \in [a_i, b_i], \ i \in [1, n] \).

(2) Individual evaluation
The individual fitness function is defined as follows:
\[
F(X,t) = [S(\theta,t) + \varphi]^{-1}
\]
where parameter \( \varphi \) refers to a small enough positive number.

(3) Selection
In order to prevent the premature convergence and stagnation, the selection method of genetic algorithm should be enhanced. Suppose that the members of the population are listed according to the size of the \( F \) value \( (X_1, X_2, \cdots, X_N) \).

(4) Crossover
Assume that \( P(X) > P_C \), and \( P_C \) denotes crossover probability. We select two parent individuals \( Pa[1] \) and \( Pa[2] \), and the child individual are illustrated as \( Ch[1] \) and \( Ch[2] \). Random numbers \( a_1, a_2, \cdots, a_n \) are created at first, and the following conditions are defined:
\[
Ch[1] \cdot chrom[j] = a_j \cdot Pa[1] \cdot chrom[j] + (1 - a_j) \cdot Pa[2] \cdot chrom[j]
\]
\[
Ch[2] \cdot chrom[j] = a_j \cdot Pa[2] \cdot chrom[j] + (1 - a_j) \cdot Pa[1] \cdot chrom[j]
\]
where \( j \in [1, n] \).

(5) Mutation
For individual \( Pa[j] \) which are less than the probability of mutation, we randomly choose one of the genes for the mutation process:
\[
Ch[i] \cdot chrom[j] = Pa[i] \cdot chrom[j] + \omega
\]
where \( \omega = \frac{\lambda}{n} \cdot N(0,1) \). \( N(0,1) \) refers to normal distribution, where \( n \) is the total number of iterations.

(6) Ending
If the following condition is satisfied, the algorithm can be ended:
\[
|S(\theta,t) - S(\theta,t+m)| \leq \xi
\]
where \( \xi \) refers to a threshold, and \( m \) denotes the evolution times.

5. Simulation. To verify the effectiveness of the proposed method, we provide a simulation in this section. The detailed simulation settings are listed in Table. 1 as follows.

In order to make performance comparison, we compare the proposed algorithm with WSNPSO [24], which is a two phase particle swarm optimization algorithm for WSN coverage maximization. Moreover, the number of wireless sensor nodes is valued in the range \([20, 100]\) with the increment ten, and the sensing field and
Table 1. Simulation settings

| Parameter       | Value          |
|-----------------|----------------|
| Sensing field   | $50 \times 50m^2$ |
| Coverage radius | 5m             |
| Number of targets | 10-60       |
| Initial population size | 60             |
| Mutation rate   | 3%             |

coverage radius are equal to $50 \times 50m^2$ and 5m respectively. Original sensor node deployments for different sensor number are listed in Fig. 2.
(a) 20 sensors
(b) 30 sensors
(c) 40 sensors
(d) 50 sensors
(e) 60 sensors
(f) 70 sensors
Fig. 2 Initial node deployment for different schemes

Coverage ratio for various number of sensors is shown in Fig. 3.
Figure 2. Initial node deployment for different schemes

Coverage ratio for various number of sensors is shown in Fig. 3.

It can be observed from Fig. 3 that that the proposed method can obtain higher coverage ratio than WSNPSO, and all these two approaches outperforms the initial coverage, which is regarded as the baseline.

Next, we use the maximum moved distance to test the performance of various methods (shown in Fig. 4).

It can be observed from Fig. 4 that to obtain higher quality of target coverage, the proposed method needs lower maximum moved distance than WSNPSO. We
It can be observed from Fig. 3 that the proposed method can obtain higher coverage ratio than WSNPSO, and all these two approaches outperform the initial coverage, which is regarded as the baseline.

Next, we use the maximum moved distance to test the performance of various methods (shown in Fig. 4).

It can be observed from Fig. 4 that to obtain higher quality of target coverage, the proposed method needs lower maximum moved distance than WSNPSO. We also can find that the proposed method consumes lower energy in the process of target coverage.

Afterwards, we will try to test the network lifetime for different node deployment policy, and the energy cost for different working states are shown in Table. 2 as follows.

| Working state | Energy cost (mA) |
|---------------|-----------------|
| Active        | 13.58           |
| Transmitting  | 14.41           |
| Receiving     | 9.37            |

Next, we test the network lifetime under different settings for different target coverage schemes.

As shown in Fig. 5, the network lifetime increases with the number of sensors increasing, because the targets covered by more sensor nodes are able to enhance the network lifetime. Furthermore, the proposed method performs very close to the optimal scheme. However, the optimal scheme is belonged to a NP-hard method, it is impossible to be used.

Fig. 6 demonstrates that network lifetime decreases when the number of targets increasing. Because with the number of targets increasing, more power consumption of sensors are required.

From the above experimental results, the conclusion can be drawn that the proposed method can effectively balance the trade-off between target coverage and energy consumption, because the proposed genetic algorithm can effectively optimize positions of all sensors.

6. **Conclusion.** This paper proposes a novel wireless sensor network energy efficient coverage method based on genetic algorithm. We aim to cover a 2D sensing
Next, we test the network lifetime under different settings for different target coverage schemes. As shown in Fig. 5, the network lifetime increases with the number of sensors increasing, because the targets covered by more sensor nodes are able to enhance the network lifetime. Furthermore, the proposed method performs very close to the optimal scheme. However, the optimal scheme is a NP-hard problem, making it impossible to be used.

Fig. 6 demonstrates that network lifetime decreases when the number of targets increases. Because with the number of targets increasing, more power consumption of sensors are required.

Figure 5. Network lifetime with various number of sensors

Figure 6. Network lifetime with various number of targets

area through choosing a minimum number of sensors, and the deployed wireless sensors should be connected to let each sensor be connected a path to the base station. The main innovation of this work lies in that we use the genetic algorithm is used to optimize the number of potential position to satisfy target k-covered and sensor m-connected. In the end, simulation results prove that the proposed method can achieve a good trade-off between target coverage and energy consumption.
In the future, we will extend the proposed method in 3D sensing area, and try to use other optimization algorithms in our research.

Acknowledgments. This work was supported in part by National High-tech R&D Program (Grant No.2015AA015303), National Natural Science Foundation (Grant No. 61272083) of China. 2017 General topic capital of online educational research fund by online education research center of Department of Education (QTONEDUCAIION) (2017YB101).

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Received July 2017; revised November 2017.

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