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Full Target K-Coverage Retention at the Boundary of Smart Sensor Networks

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The presence of a large amount of redundant data in smart wireless sensor network coverage can lead to problems such as low coverage. Hence, this study proposes a holding protocol applied to the all-target k coverage of smart sensor networks. In this study, firstly, the relationship between target nodes and sensor nodes is determined with the help of the network model, and the theorem and argument process related to coverage quality is analyzed to determine the solution of coverage expectation value in the monitoring area. Then, the energy conversion process of sensor nodes is analyzed in combination with related definitions. Finally, the MTCPP algorithm is constructed to maintain the bounded all-target k coverage of the network. Test results confirm that the MTCCP algorithm outperforms the other three network coverage algorithms. The running time of all four network coverage algorithms gradually increased as the number of sensor nodes and the number of target nodes gradually increased. The number of sensor nodes gradually increased with the increase of network coverage, and the MTCCP algorithm improved the network coverage by 17.65%, 15.46% and 13.26% compared with the OCES, ETCA and EPDM algorithms for the same number of sensor nodes. The MTCPP algorithm has a higher network coverage and energy-consuming network survival cycle, and can be applied to smart wireless sensor networks for the monitoring of target retention, which is of great value in the fields of surveillance and transportation.

Keywords: smart sensors; k re-coverage; energy conversion; network survivability; MTCCP

1. INTRODUCTION

A smart wireless sensor is a self-organized, distributed network, comprising computing power, communication, sensing and many other sensor node components enabling it to monitor in real time a diverse range of environmental information and events; it has unsupervised, high flexibility, large scale and other characteristics to capture comprehensive, accurate, real-time data to achieve effective target tracking and area monitoring [1–2]. Currently, smart wireless sensors are being widely used in traffic control, electronic medical, environmental monitoring and other fields. The most fundamental issue for smart wireless sensors is network coverage, which not only indicates the movement of all targets in the target monitoring area, but also the quality of service provided by the network. Smart wireless sensor networks have very limited power storage due to their small size, making energy consumption issues a challenge for current research [3–4]. Most of the research related to energy consumption and energy saving in smart wireless sensor networks focuses on sensor node activity scheduling, data compression, energy efficient data propagation and aggregation, data transmission energy control, energy-aware routing protocols, etc. The mature approaches are data compression, dormant scheduling, and routing protocols. In order to improve the coverage of smart wireless sensor networks and reduce coverage voids, the study proposes a coverage preservation protocol combining all-target k in order to achieve high-quality, real-time monitoring of smart sensor networks.

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2. REVIEW OF THE LITERATURE

Sun and Li [5] proposed a collaborative optimized coverage algorithm based on the sensor cloud system in smart computing in order to prevent the limitation of coverage of traditional wireless sensor networks on data size and node energy, which optimizes the clustering through the controllable threshold parameter and variance parameter, thereby making the nodes more uniformly clustered. Simulation results show that the algorithm proposed in the study outperforms other algorithms in terms of network survival time and network coverage, and is highly effective and stable. Karatas and Onggo [6] optimized barrier coverage for wireless sensor networks with hub-and-spoke topology by means of a mathematical and simulation model that takes into account budget constraints, network topology, communication interference, communication range, sensor reliability, probabilistic detection function, target type, etc. Experimental results showed that the proposed model has more accurate results and is able to solve the barrier coverage problem well. Xu [7] used an elite adaptive particle swarm algorithm to solve the target coverage problem of high-density wireless sensor networks, and evaluated the monitoring rate of the network through the system model. The statistical simulation results showed that the elite adaptive particle swarm algorithm has better performance. Zhang et al. [8] proposed a serial and threshold-based maximum logarithmic message-passing algorithm for multimode detection to address the problems of multi-node complexity and low accuracy in smart wireless sensor networks. The simulation results showed that the algorithm achieved a good balance between accuracy and complexity reduction rate, significantly changing the algorithmic complexity reduction rate for multi-node detection in the system. In order to solve the problem in intelligent fault detection, Gutiérrez and Ponce [9] investigated and proposed a supervised learning method known as artificial hydrocarbon networks to predict temperature and detect faults in remote location sensor nodes by comparing them with field temperature sensors. Their proposed method is able to accurately identify and address sensor faults.

Wang et al. [10] proposed an efficient intelligent data fusion algorithm for wireless sensor networks limited by hard-to-charge battery packs, fusing redundant data through cluster routing to reduce the amount of data sent to the base station or aggregation nodes. Simulation results showed that the proposed fusion algorithm outperformed other common network consumption algorithms in terms of network survival and energy consumption. Hu et al. [11] proposed an intelligent data fusion algorithm based on genetic algorithm and particle swarm optimization algorithm in order to improve the energy utilization and extend the survival time of wireless sensor networks, an optimized backpropagation neural network data fusion algorithm based on genetic algorithm and particle swarm optimization algorithm was proposed. Experimental results showed that the proposed algorithm was effective in reducing network communication, saving node energy consumption and extending network lifetime. Sevgican et al. [12] used machine learning algorithms to predict intelligent network data The simulation test results showed that the neural network algorithm outperformed linear regression in terms of network load prediction. Ding et al. [13] proposed an intelligent method for short-term flashover fault detection in high-power mains power systems, using wavelet-type wavelet packet energy moments to extract short-term flashover fault characteristics of high-power mains power systems. Mann and Singh [14] analysed the problem of efficient clustering in wireless sensor networks and proposed an improved artificial bee colony metaheuristic algorithm to improve the exploitation capability of existing metaheuristics by improving the solution search equation. Simulation results showed that the clustering protocol outperformed other well-known protocols in terms of performance metrics such as packet delivery rate, throughput, energy consumption, network survival time and delay. Lorenz et al. [15]have proposed a new method for the centrality of deployment paths in wireless sensor networks for operator evolution, and the results show that the method is extremely practical and feasible.

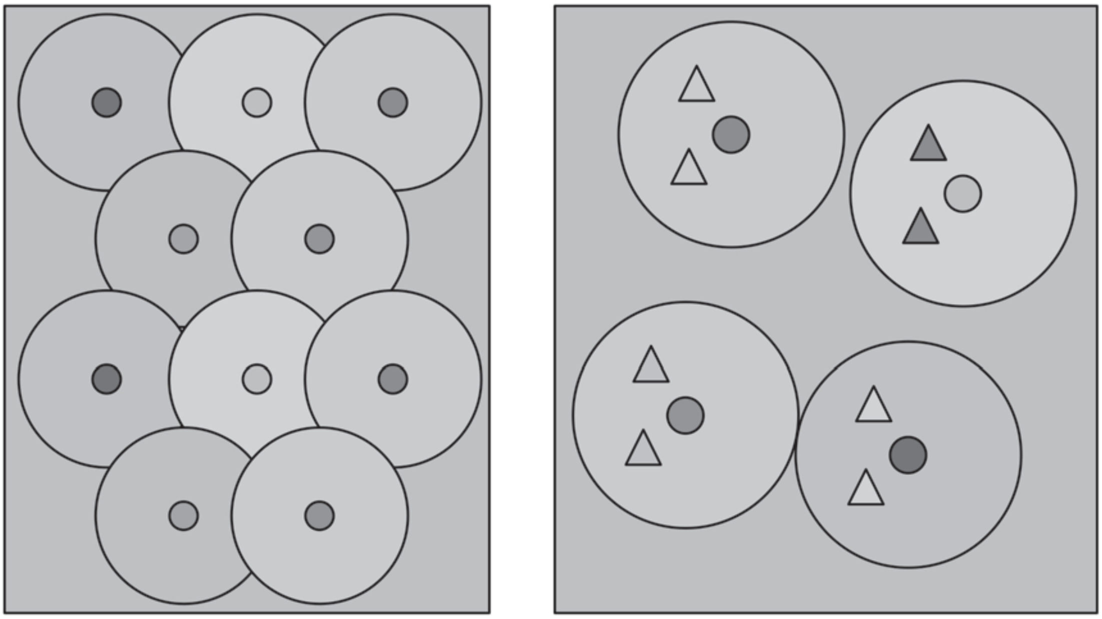
Previous research on smart sensor networks has focused mainly on the analysis and exploration of network coverage problems. However, despite certain achievements in related network coverage problems, research on target boundary coverage is relatively rare, and there is almost no discussion about network boundary k re-coverage retention. The current study proposes an all-target k re-coverage retention protocol applied to smart sensor network boundaries, aiming to improve network coverage and maintain the integrity of network target tracking.

3. WIRELESS SENSOR NETWORK BOUNDARY FULL TARGET *K* COVERAGE RETENTION TECHNOLOGY

3.1 Theoretical Assumptions and Network Model

Based on previous research on coverage optimization algorithms for smart sensor networks, this study proposes a combined multi-objective coverage-preserving protocol (MTCPP). This protocol serves as an expectation value coverage calculation method that enables energy conversion of the whole network. The expected value is achieved by the slave relationship between sensor nodes and all-objective nodes, and the energy conversion is calculated by the scheduling mechanism of the sensors. The protocol guarantees the quality of coverage of the network, as well as the homogeneity and balance of the network energy [16–18]. In order to better analyse the MTCPP and the smart wireless sensor coverage problem, this study makes the following assumptions. One, all nodes in the smart sensors are in operation, they all have a certain degree of sensing capability and the communication and sensing range is disc-shaped. Two, the side length of the monitoring area exceeds the sensing radius of all sensors. Third, the energy of all sensor nodes does not differ at the initial moment and is consistent with the hour hand. Fourthly, the sensor nodes' location information is accurately obtained via GPS. Fifth, all sensing radii are in a normal distribution pattern.

After making five aforementioned assumptions, the study gives the definitions of target coverage, k coverage, network lifetime, and coverage quality. The coverage problem of smart



《a》Schematic diagram of area coverage

《b》Schematic diagram of point coverage

Figure 1 Schematic diagram of area coverage and point coverage.

wireless sensors involves target coverage, area coverage (the most common mode), and fence coverage. Setting the two-dimensional plane as $\mho$, an area being completely covered means that all points in $\mho$ are covered by one or more sensor nodes. Similarly, a region $\mho$ covered by k means that all points are covered by $\mho$ k or more sensor nodes. Based on the definition of a 2D plane, the definition of a 3D spatial coverage is as follows. A space covered by k is when any point in this space is covered by a sensory disc of k sensor nodes. Figure 1(a) shows a schematic representation of the area coverage. Common coverage problems for smart wireless sensors are area coverage, point coverage, and fence coverage. Point coverage applies when it is not necessary to focus on the whole area, but only on the discrete points in the area.

The fence coverage differs from the other two coverage methods in that the study of this coverage method no longer focuses on detecting the specific types of events that occur within the target; it monitors a small area of target movement. This point coverage is shown schematically in Figure 1(b). Network survival time is determined by the difference between the moment the network starts to operate and the moment when the smart wireless sensors in the network are no longer able to detect the target. The quality of coverage in a two-dimensional plane is the ratio of the sum of the sensor nodes' sensing surfaces to the region within the monitored area.

Generally speaking, smart wireless sensor network coverage can be divided into two types: deterministic coverage and random coverage, depending on the different objects covered by the sensor nodes and the number of sensor nodes. In deterministic coverage, attributes such as the location and deployment of each node are determined before the wireless sensor network is built, and the nodes are deployed according to known information, specifically the density of nodes and their location in the target area. In stochastic coverage, the distribution of nodes and the location of each node are not determined before the construction, and is usually used in harsh environments and when there are a large number of nodes in the target area. It is widely used in many fields such as natural disaster prevention and control, hazard target control, etc. Accordingly, the study uses a stochastic coverage approach in the analysis of the area coverage problem [19–20]. The random distribution of smart sensor nodes follows a chi-square Poisson point process with node density λ. The Poisson point process is explained as follows. The Poisson point process with the parameter λ in the Borel event set $B(X)$ is set to satisfy the following two characteristics. One, an arbitrary subset of A on $B(X)$ with the coverage of the random variable $P(n(A) = k)$ as Equation (1).

$$P(n(A) = k) = e^{-\lambda|A|}(\lambda|A|)^k/k! \tag{1}$$

In Equation (1), $n(A)$ is the number of nodes and the measure of A is $|A|$. Two, the two subsets A_1 and A_2 of $B(X)$ are considered to be independent of each other, assuming that they do not intersect. The smart wireless sensor network is modelled in the following way: a network consisting of N sensor nodes is set up, with the combination of nodes represented by $V = \{v_1, v_2, \ldots v_N\}$ and all nodes having the same structure. Each node in the network has its own unique identification number, and all nodes have the same communication radius R_c and sensing radius R_s. The nodes are set up with a random distribution in the target area in the two-dimensional plane and a disk in the sensing area R_s for each node, while the node can communicate with any neighboring node within its communication range. Based on the definition of network coverage and connectivity, the study sets the parameter $R_c = 2R_s$ for subsequent studies. It is assumed that two nodes in the set of nodes are represented by v_i and v_j; when the Euclidean distance between them is $d_{i,j} \leq R_c$, the two nodes are called neighboring nodes. Each node in the network is not able to determine its own exact

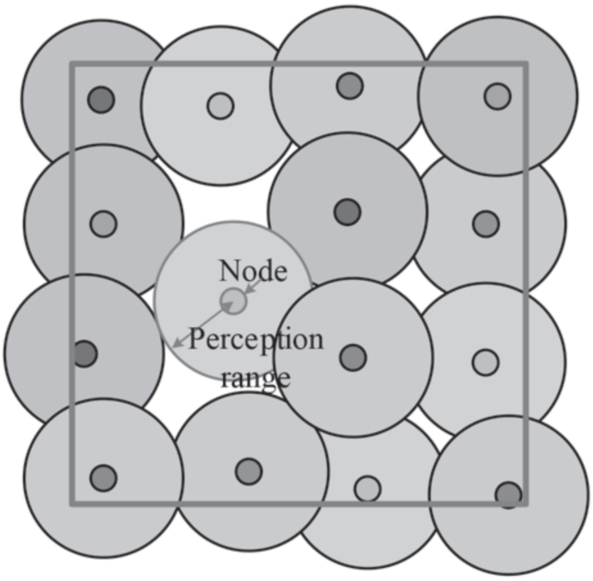


Figure 2 Schematic diagram of network model.

position, but neighboring nodes can make a judgement about the relative position information after communicating with each other, and the distance information is obtained by the distance measurement method. Two assumptions need to be made in the network model constructed for the study [21–22]. One, the target area is set to be a square area and the perceived range of the node v_i is a disk D_i. There are no two nodes at exactly the same location in the network and each node has a different identification number. Second, the boundary is completely covered by the node. Nodes in the network that are in non-boundary areas are internal nodes; otherwise, they are column nodes. Figure 2 is a schematic representation of the finger network model.

3.2 Steps for Implementing the MTCCP Algorithm in Wireless Sensor Networks

To facilitate the implementation and analysis of the MTCCP algorithm in subsequent wireless sensor networks, the study first introduces the network coverage quality and energy conversion. There are two theorems related to network coverage quality, one of which is to set the coverage of any sensor node as p, when k is covered, assuming $k = 2$, the number of sensor node moves as m and n, the corresponding probability of occurrence as p^2q^{n-2} and the conditional probability as pq^{n-m-1}, where $q = 1-p$. The corresponding inference process is as follows: X and Y are the number of nodes moved in rounds 1 and 2 respectively. The occurrence probability of smart wireless sensor nodes is calculated using Equation (2).

$$P(X = m, Y = m) = p^2q^{n-2} \tag{2}$$

Equation (3) is used to calculate the joint probability of the first round.

$$p \tag{3}$$

The expression for the joint probability of the second round is obtained with Equation (4).

$$P(X = n) = \sum_{m=1}^{n-1} P(X = m,\ Y = n) = \sum_{m=1}^{n-1} p^2q^{n-2} \\ = (n-1)p^2q^{n-2} \tag{4}$$

The formula for conditional probability can be obtained by referring to the multiplicative formula for probability, as in Equation (5).

$$P(Y = n|X = m) = (P(X = m,\ Y = n))/P(X = m) \\ = p^2q^{n-2}/pq^{m-1} = pq^{n-m-1} \tag{5}$$

Theorem 2 is as follows: the two-dimensional plane sensor node coverage is p, the maximum number of consecutive sensor node coverage is J, and the cut-off mobile target node is fully covered. The expected value of sensor node coverage is calculated by Equation (6).

$$E(X) = \left[1 - (1-p)^J\right] p^{-1} \tag{6}$$

The maximum number of consecutive sensor nodes covered is H and X is the number of transfers of the target node, which can be taken as $X \in [1, 2, \cdots, N]$. Based on the probability theory, the expression of the distribution density function of X can be calculated as Equation (7).

$$P(X = k) = \begin{cases} p(1-p)^{k-1} & k = 1, 2, \cdots, H-1 \\ (1-p)^{H-1} & k = H \end{cases} \tag{7}$$

Therefore, it can be deduced that the sensor node coverage expectation can be found with Equation (8).

$$E(X) = \sum_{k=1}^{H-1} kp(1-p)^{k-1} + H(1-p)^{H-1} \tag{8}$$

Equation (9) is further obtained by processing the mathematical formula.

$$E(X) = p\left(\frac{1-(1-p)^{H-1}}{p^2} - \frac{(H-1)(1-p)^{H-1}}{p}\right) \\ + H(1-p)^{H-1} = \left[1 - (1-p)^J\right] p^{-1} \tag{9}$$

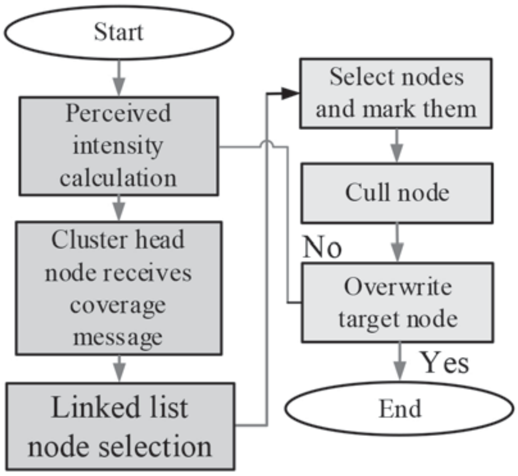


Figure 3 Schematic diagram of MTCCP algorithm implementation.

For energy conversion, the energy consumption is generated for both the communication and sensing modules. The energy consumption of the sensing module $E_T(l, d)$ is calculated with Equation (10) when the data is collected at l bits.

$$E_T(l, d) = \begin{cases} lE_{T-elec} + l\theta_{fs}d^2 \; d < d_0 \\ lE_{T-elec} + l\theta_{amp}d^4 d > d_0 \end{cases} \tag{10}$$

In Equation (10), d_0 and d are the threshold value for the communication distance between sensor nodes and the communication Euler distance, respectively, and l is the fixed transmission data length. When the distance between sensor nodes is less than d_0, the energy attenuation factor θ_{fs} is 2; otherwise, the value θ_{amp} is 4.

The energy consumption model of the receiver module is calculated with Equation (11).

$$E_R(l) = E_{R-elec}(l) = lE_{elec} \tag{11}$$

There are three concepts in energy conversion: optimal subset, energy properties, and maximum distortion. Setting the set of smart wireless sensor nodes as D, the optimal subset can be understood as all sensor nodes in the subset of sensor nodes are completely covered by the target per unit of time. Based on the coverage compliance, the maximum distortion amount is calculated by Equation (12).

$$E\left[\left(s_1(x, y) - s(x, y)^2\right)\right] \le D \tag{12}$$

In Equation (12), $s_1(x, y)$ and $s(x, y)$ are the estimated, measured mean values of the Euclidean distance between the sensor node and the target node, respectively. The energy conversion includes a theorem that the difference between the distance and the variance between the communicating nodes is 0 or negative compared to the difference of half of the distortion. Assume that the measurement at the target node $t(x, y)$ is $s(x, y)$ and that the resulting data information covers the measurement data. During the measurement of the target node, the measurement mean needs to meet the following conditions, all of which are consistent with the normal distribution $(u, \sigma^2) \cdot u$ is the mean value and σ is the standard error. $W\{w_1, w_2, \cdots w_n\}$ is the energy sensor node energy set and the Euclidean distance between communication nodes is Equation (13).

$$R((x_1, y_1), (x_2, y_2)) = \sqrt{(x_1 - x_2)^2 + (y_1, y_2)^2} = R(d) \tag{13}$$

Assuming that the collection of acquisition data information is H, the complementary set is referred to as H_1 and one of the signal data in H_1 is estimated from the measurement closest to the target node, H. The estimated value of the signal at the target node is $s_1(x_0, y_0)$ and can be expressed with Equation (14).

$$s_1(x_0, y_0) = s(x_1, y_2) \tag{14}$$

Equations (13) and (14) are combined to yield Equation (15).

$$R(d) \le \sigma^2 - D/2 \tag{15}$$

Essentially, the MTCCP algorithm divides the coverage in the monitoring area into multiple areas applying the theory of cluster technology, and each cluster head node manages and controls the member nodes within the cluster. The flow chart is shown in Figure 3. Firstly, the sensing intensity of the cluster members is calculated; then, the cluster member nodes send k coverage to the cluster head node which will receive the messages from all members within a few time units; secondly, the cluster head node constructs a chain table in which all information is regrouped, arranged and stored. The sensing nodes need to be sorted according to the energy size, and the nodes with higher energy are given weights. Secondly, when the target node is covered by k, the cluster head node will eliminate the sensor nodes with weaker sensing strength and traverse the chain table, which will use the best subset to cover the target node via the cluster head node; otherwise, the operation will be repeated.

4. EFFECTIVENESS OF THE MTCCP ALGORITHM IN INTELLIGENT WIRELESS SENSOR NETWORKS

In order to verify the feasibility and effectiveness of the MTCCP algorithm in smart wireless sensors, MATLAB was

Table 1 Simulation parameters and values.

Parameter	Numerical value	Parameter	Numerical value
Monitoring area/m^2	400 × 400	Monitoring radius /m	40
Learning rate	0.001	Maximum energy attenuation coefficient	100
Effective monitoring radius/m	20–40	Minimum energy attenuation coefficient	10
Maximum running time/s	600	Energy consumption of receiving module	50
Initial energy/J	10	Energy consumption of sensing module	50

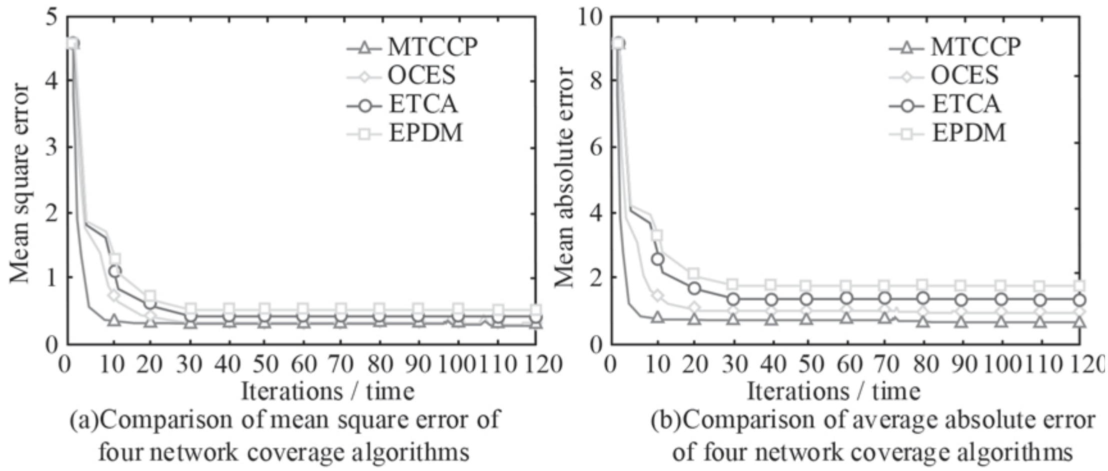


Figure 4 Comparison results of mean square error and mean absolute error of four network coverage algorithms.

used as the simulation platform, all sensors were set to have the same structure, each sensor had three sensing directions, the monitoring areas did not overlap each other, the unit of network survival cycle was rounds, the final result was the average result of 30 runs. All the parameters and values used are shown in Table 1.

The study uses Optimization Coverage of Wireless Sensor Networks Based on Energy Saving (OCES), Coverage based on event probability driven mechanism (ETCA), and Energy efficient target coverage algorithm (EPDM) as comparison algorithms to determine the performance of the MTCCP algorithm. The mean square error and mean absolute error are shown in Figure 4(a) and Figure 4(b) respectively. The mean square error of the MTCCP algorithm is almost a straight line until the number of iterations is 20, and the convergence speed is rapid; however, the convergence speed becomes slower in the interval of 20–40 iterations, and the final convergence number is 40, and the stable value of the mean square error is 0.23. The mean square error of the other three network coverage algorithms of OCES, ETCA and EPDM is higher than that of MTCCP. As shown in Figure 4(b), the convergence trend of the mean absolute error and the mean square error of the MTCCP algorithm are similar, and the convergence value of the mean absolute error is higher than that of the other three network coverage algorithms. the convergence value of the MTCCP algorithm is 0.83, while the convergence values of the OCES, Therefore, the mean square error and mean absolute error of the MTCCP algorithm are better than those of the other three algorithms.

The experiments were conducted separately to compare the accuracy under different search area conditions. The results of the four network coverage algorithms are shown in Figures 5(a)–5(d) respectively. Of the four network coverage algorithms, the MTCCP showed the best accuracy rate in the three types of target search processes, namely general target scale, small target scale and minimum target scale, with the highest values of 98.7%, 87.2% and 89.4% in the three target searches, and the corresponding best search ranges of 3.8 m, 3.2 m and 2.9 m. This further validates the accuracy of the MTCCP in searching for targets of various scales at the regional level.

Figure 6(a) shows the network survival period for different numbers of sensor nodes. As the number of sensor nodes increases, the network survival period of the four network coverage algorithms also shows a gradual increase, but the OCES, ETCA and EPDM algorithms increase more slowly. This is because they all monitor the whole network through a centralized approach, which consumes more node energy; whereas the MTCCP algorithm covers the whole target by finding the best set through a chain table. At a sensor node count of 300, the MTCCP algorithm network survival time is 486.5s, which is 16.53%, 23.56% and 26.87% better compared to OCES, ETCA and EPDM algorithms respectively. Figure 6(b) shows the network survival period for different number of target nodes. Along with the increase in the number of target nodes, the network survival period of the four algorithms gradually decreases, and the MTCCP algorithm has an improvement of 7.86%, 8.63% and 9.65% compared to the network survival time of OCES, ETCA and EPDM, respectively.

Figures 7(a) and 7(b) show the network runtime of the four network coverage algorithms with different numbers of sensor nodes and target nodes. Overall, the runtime of all four algorithms increases gradually for different numbers of sensor nodes and target nodes, but the MTCCP algorithm has

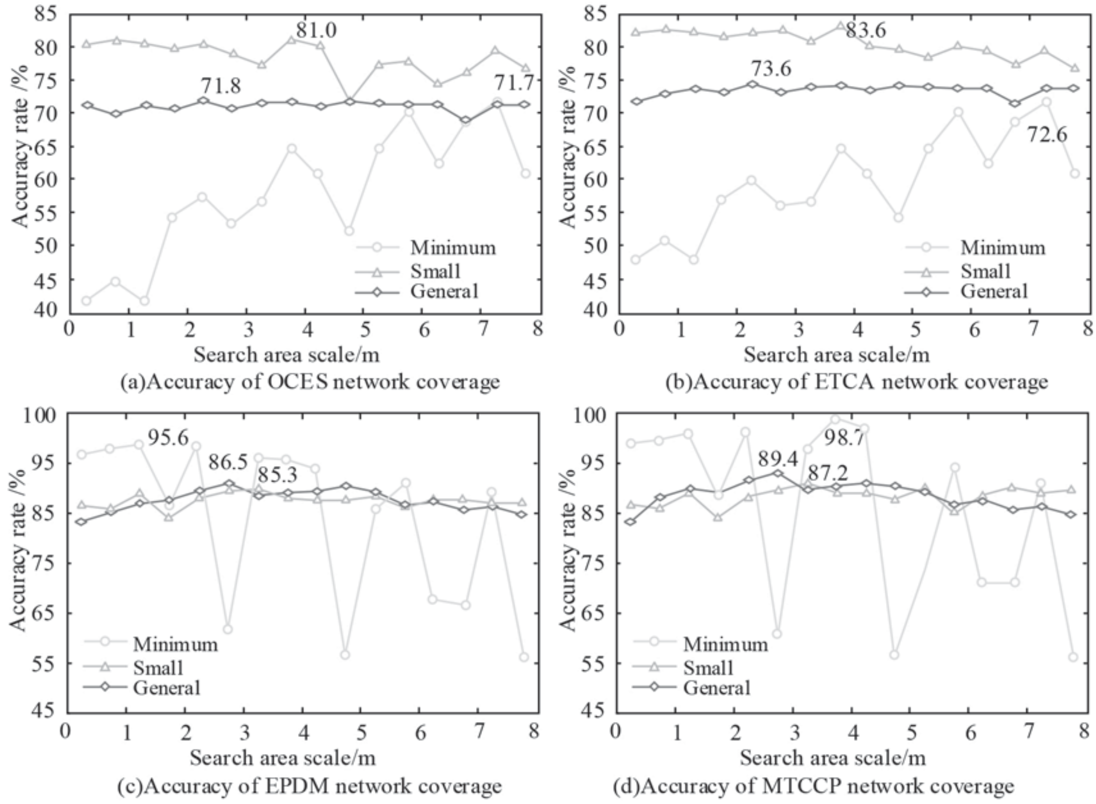


Figure 5 Accuracy of four network coverage algorithms in different monitoring areas.

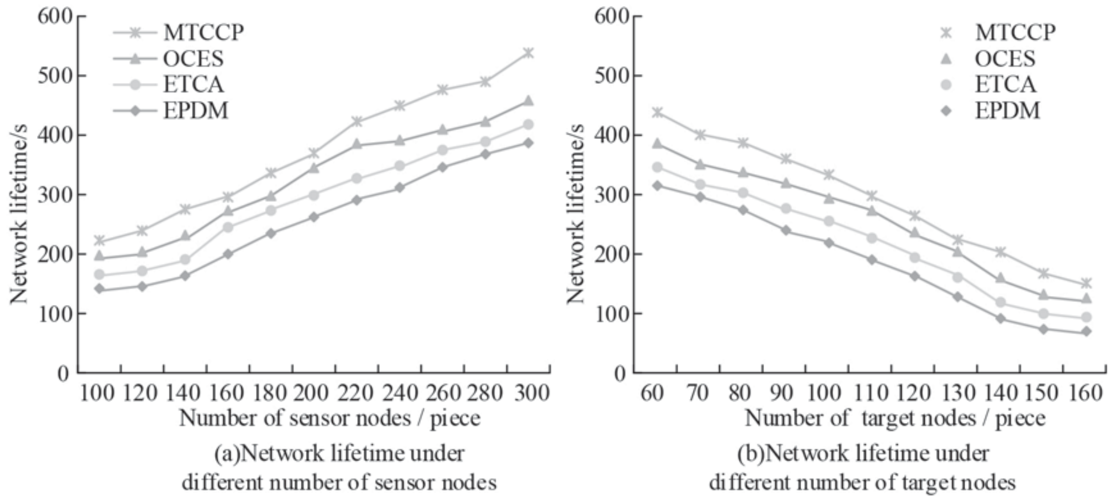


Figure 6 Network lifetime under different number of sensors and target nodes.

the shortest runtime with the same parameters because it uses a clustered structure and is efficient in finding sensor nodes that meet the coverage conditions.

Figure 8 shows the number of sensor nodes at different network coverage rates for the four network coverage algorithms. The number of sensor nodes gradually increases as the network coverage increases, and when the network coverage reaches 99.9%, which can be interpreted as full coverage of all target nodes, the number of active nodes for the MTCCP, OCES, ETCA and EPDM algorithms are 135, 175, 190 and 155 at this time. with the same number of sensor nodes, the MTCCP algorithm compares to the same number of sensor nodes, the MTCCP algorithm improves the network coverage by 17.65%, 15.46% and 13.26% compared to the OCES, ETCA and EPDM algorithms.

Setting the number of sensors in the directed sensor network to 150, Figure 9(a) shows the impact of the sensing radius on the network survival. Overall, compared to other network coverage algorithms, the MTCCP algorithm has a longer network survival period for the same sensing radius. When the sensing radius is 36m, the MTCCP algorithm has a more pronounced effect on network survival. Figure 9(b) shows the effect of the number of sensing directions on network survival. With a sensing radius of 20m, the MTCCP algorithm has a more pronounced effect on network survival when the number of sensing directions is 4.

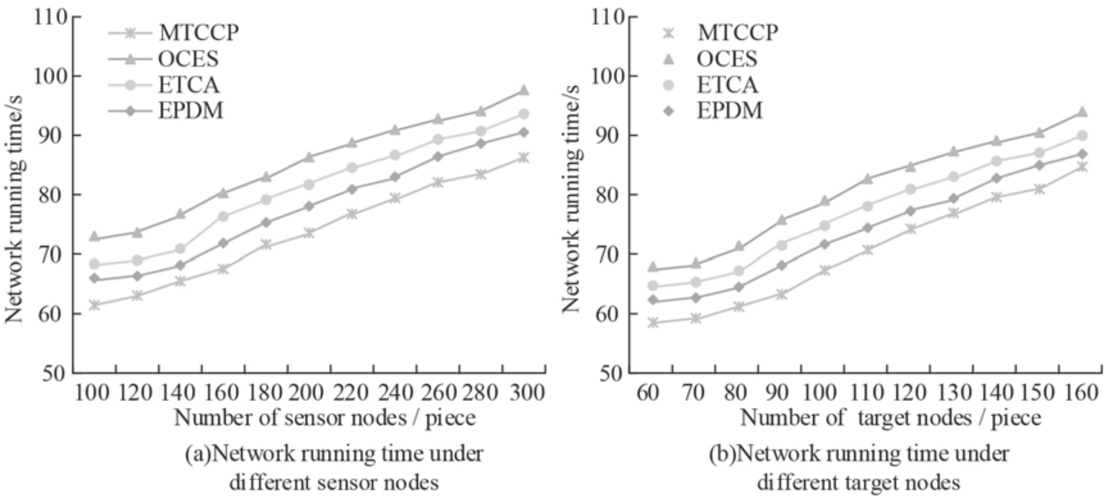


Figure 7 Network running time under different sensors and target nodes.

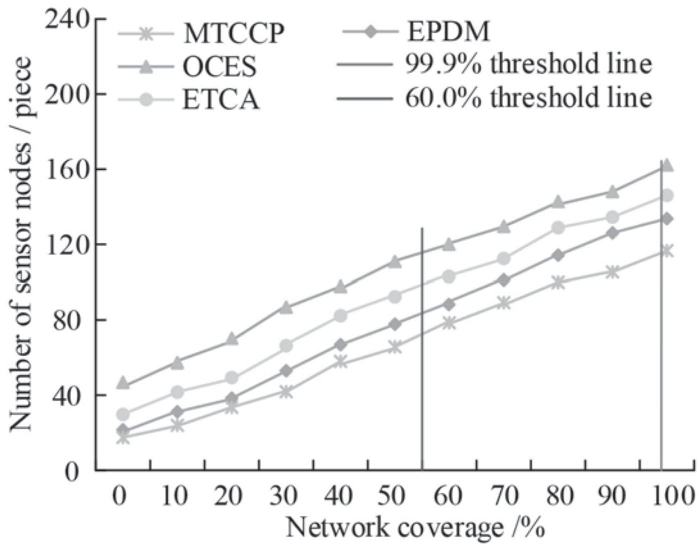


Figure 8 Number of sensor nodes with different network coverage of four network coverage algorithms.

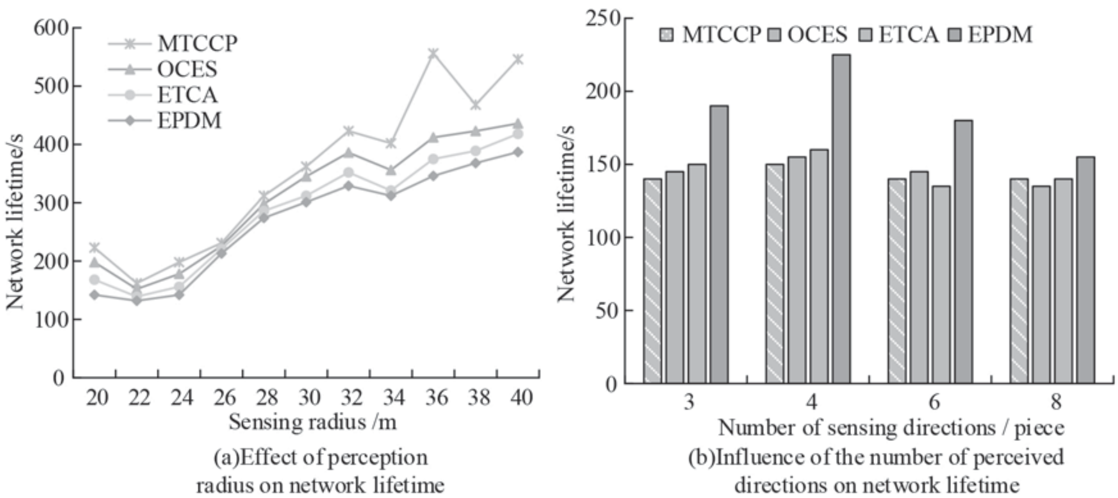


Figure 9 Influence of perceived radius and number of perceived directions on network lifetime.

5. CONCLUSION

Full target coverage by smart sensors requires a large amount of energy and reduces the effective coverage area, which can lead to a series of situations including ineffective target coverage monitoring and coverage voids. The improvement of network coverage and prevention of the void effect are the focus of this current research, and an MTCCP algorithm for full target boundary coverage is designed. The simulation results show that, compared with other network coverage algorithms, the MTCCP algorithm converges at 20 iterations, and the mean square error and mean absolute error are 0.23 and 0.83 respectively; the best search range of the algorithm is 3.8m, 3.2m and 2.9m for three types of targets: general target, small target and minimum target scale, and the corresponding accuracy rate is the highest at this time. The network survival period of the four network coverage algorithms gradually increases as the number of sensor nodes increases, and decreases as the number of target nodes increases. Compared to the network survival time of the three algorithms of OCES, ETCA and EPDM, the MTCCP algorithm improved by 7.86%, 8.63% and 9.65% at the number of target nodes 60, respectively. The number of sensor nodes gradually increases with the increase of network coverage. When the network coverage reaches 99.9%, which can be interpreted as the full coverage of all target nodes, the number of active nodes of MTCCP, OCES, ETCA and EPDM algorithms are 135, 175, 190 and 155 at this time. It can be seen that the MTCCP algorithm in the smart wireless sensor network boundary Full Target k coverage maintenance is effective and feasible. However, the study has one major shortcoming in that the non-linear coverage of irregular monitoring areas is not considered.

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REFERENCES

1. Liu Y. Research on intelligent fusion method of multisensor data in Internet of Things. 2019. *Electrical Engineering and Automation: Chinese and English version, 8*(1): 5–8.
2. Almarashdeh I, Alsmadi M K, Farag T, et al. 2018. Real-time elderly healthcare monitoring expert system using wireless sensor network. International *Journal of Applied Engineering Research, 13*(6): 3517–3523.
3. Prabha M, Darly S S, Rabi B J. 2021. A novel approach of hierarchical compressive sensing in wireless sensor network using block tri-diagonal matrix clustering. *Computer Communications, 168*(2): 54–64.
4. Muduli L, Mishra D P, Jana P K. 2018. Application of wireless sensor network for environmental monitoring in underground coal mines: A systematic review. *Journal of Network and Computer Applications*, 106: 48–67.
5. Sun Z, Li Z. 2020. CoC-SCS: Cooperative-optimization coverage algorithm based on sensor cloud systems in intelligent computing. *IEEE Access*, 8: 129058–129074.
6. Karatas M, Onggo B S. 2019. Optimising the barrier coverage of a wireless sensor network with hub-and-spoke topology using mathematical and simulation models. *Computers & Operations Research*, 106: 36–48.
7. Xu M, Zhou J, Lu Y. 2019. Elite adaptive particle swarm optimization for target coverage problem in high-density wireless sensor networks. *Journal of Physics Conference Series*, 1267: 012006–012012.
8. Zhang G, Gu Z, Zhao Q, et al. 2020. A multi-node detection algorithm based on serial and threshold in intelligent sensor networks. *Sensors (Basel, Switzerland), 20*(7): 1960–1972.
9. Gutiérrez S, Ponce H. 2019. An intelligent failure detection on a wireless sensor network for indoor climate conditions. *Sensors, 19*(4): 854–872.
10. Wang H, Song L, Liu J, et al. 2021. An efficient intelligent data fusion algorithm for wireless sensor network. *Procedia Computer Science, 183*(3): 418–424.
11. Hu Q, Wang H, Di N, et al. 2018. Implementation and simulation analysis of an intelligent data fusion algorithm in wireless sensor network. *Chinese Journal of Sensors and Actuators, 31*(2): 283–288.
12. Sevgican S, Turan M, Gokarslan K, et al. 2020. Intelligent network data analytics function in 5G cellular networks using machine learning. *Journal of Communications and Networks, 22(*3): 269–280.
13. Ding Y, Jin H, Fan M. 2019. Research on intelligent detection technology of short-term flashover fault in high-power main network power systems. *Journal of Physics Conference Series*, 1345: 052044–052049.
14. Mann P S, Singh S. 2019. Improved metaheuristic-based energy-efficient clustering protocol with optimal base station location in wireless sensor networks. *Soft Computing, 23*(3): 1021–1037.
15. Syarif A, Abouaissa A, Idoumghar L, et al. 2019. New path centrality based on operator calculus approach for wireless sensor network deployment. *IEEE Transactions on Emerging Topics in Computing, 7*(1): 162–173.
16. Cao B, Zhao J W, Yang P, et al. 2018. 3-D multiobjective deployment of an industrial wireless sensor network for maritime applications utilizing a distributed parallel algorithm. *IEEE Transactions on Industrial Informatics, 14*(12): 5487–5495.
17. Goyal N, Dave M, Verma A K. 2019. Data aggregation in underwater wireless sensor network: recent approaches and issues. *Journal of King Saud University-Computer and Information Sciences, 31*(3): 275–286.
18. Ziaur R, Fazirulhisyam H, Rasid M, et al. 2018. Totally opportunistic routing algorithm (TORA) for underwater wireless sensor network. *PLoS ONE, 13*(6): e0197087-e0197114.
19. Wang M, Xu H, Zhou X. 2018. Cooperative dynamic game-based optimal power control in wireless sensor network powered by RF energy. *Sensors, 18*(7): 2393–2402.
20. Han Y, Zhang J, Sun D. 2018. Error control and adjustment method for underwater wireless sensor network localization. *Applied Acoustics*, 130: 293–299.
21. Dey N, Ashour A S, Shi F, et al. 2018. Developing residential wireless sensor networks for ECG healthcare monitoring. *IEEE Transactions on Consumer Electronics, 63*(4): 442–449.
22. Huang G, Zhang Y, He J, et al. 2018. Fault tolerance in data gathering wireless sensor networks. *Computer Journal, 2018*(6): 976–987.