Journal of Network Intelligence ©2020 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **5**, Number **2**, May **2020**

A Spatial Correlation Based Partial Coverage Scheduling Scheme in Wireless Sensor Networks

Jing Zhang

College of Information Science and Engineering
Institute of Artificial Intelligence
Fujian Provincial Key Laboratory of Big Data Mining and Applications
Fujian University of Technology, Fuzhou, China
33th Xueyuan Road, University Town, Minhou, Fuzhou, Fujian, 350118, China
jing165455@126.com

Hongrui Nian

College of Information Science and Engineering
Fujian University of Technology, Fuzhou, 350118, China
nhr1101@163.com

Xiucai Ye

Department of Computer Science
University of Tsukuba, Tsukuba, 3058573, Japan
yexiucai2013@gmail.com

Xiaorong Ji

College of Information Science and Engineering
Fujian University of Technology, Fuzhou, 350118, China
22459338@qq.com

Yao He

College of Information Science and Engineering
Fujian University of Technology, Fuzhou, 350118, China
wonderkewen@163.com

Received July 2018; revised August 2019

Abstract. *Wireless Sensor Networks are formed by a mass of various sensors, they are adopted in lots of applications. Because of the existence of spatial correlation in WSNs, the information from some geographic independence sensors are more significant than that from high correlation ones. Thus, it is unnecessary to transmit information from every sensor to the sink node. This paper focus on the coverage area for data monitoring in WSNs. To construct the virtual backbone network, we propose an efficient connected dominating set construction method based on clique, by taking advantage of the high spatial correlation characteristics of clique construction. Furthermore, by minimizing the number of sensors to activate, we propose a Spatial Correlation based partial Coverage Scheduling Scheme (SCCS) to prolong the network lifetime. The corresponding experiment indicate the efficiency and the feasibility of the proposed SCCS scheme. Moreover, this algorithm is able to guarantee better performance by comparing to the existing schemes.*

Keywords: Wireless Sensor Networks, clique, connected dominating set, partial coverage scheduling

---

1. **Introduction.** Wireless Sensor Network (WSN) is a typical self-organization network, which can be utilized in a variety of situations such as environmental monitoring and surveillance [1, 2, 3, 4, 5, 6]. The network performance and lifetime are critical concerns in many typical applications [7], [8]. Since the sensors are usually placed in the extreme environment, it is difficult to change the batteries for the sensors. Since some area do not have event information for collected, many sensors will be wasted. Due to the existence of spatial correlation in WSNs [9], the information from some geographic independence sensors are more significant than that from high correlation ones. Thus, it is unnecessary to transmit information from every sensor to the sink node. Less sensors can be utilized for monitor area based on spatial correlation. Then, the energy consumption can be reduced and the network lifetime can be prolong. Furthermore, the monitor area coverage is used, which is one of the three main different class coverage problems [10].

In order to monitor the whole or partial interesting area, usually the density of the WSN is high. As a result, in the same monitor area, several sensors sensing the same events. These sensing information in the sensors are similar to each other. Give a threshold, within the range of the threshold, those whose information are similar form a cluster, then one sensor need to be waked to transmit the information. Since the spatial correlation and the distance have an inverse relationship, one Connected Dominating Set (CDS) based backbone can be used in the scheme. CDS has been widely used in WSNs [11, 12].

Most of the researches focus on full coverage sleep scheduling scheme according to different user requirements. However, due to the partially distribution of target sensing data and the existence of spatial correlation in WSNs, full coverage is unnecessary. In this paper, we apply the spatial correlation levels and a feedback from sink to create the virtual backbone, to schedule the activity of its neighbor sensors. The contributions of this paper are summarized as follows:

1. A novel spatial correlation based CDS algorithm is designed, which has lower computational complexity compared to the existing coverage scheduling algorithms. The maximal independent set problem is transformed to that of finding the maximal clique. One clique base CDS construction method is utilized to minimize the independent set size.
2. In order to prolong the network lifetime, we propose a novel **Spatial Correlation Based Partial Coverage Scheduling Scheme (SCCS)** by duty cycle under the realistic WSNs. Alternative sensors are in a restricted range and locally reconstructing a CDS within the restricted range. Each CDS active in any given time to monitor the network area with the desired percentage of coverage. Furthermore, SCCS is able to maintain both coverage and connectivity.

The rest of this paper is organized as follows. Section 2 shows the related works. Section 3 gives the problem statement and preliminaries. Section 4 presents the proposed SCCS. Section 5 gives simulation of the proposed method, and Section 6 summarizes the results.

2. **Related work.** Duty cycle scheduling scheme is always utilized as a primary approaches for exploring the lifetime problem in our previous literatures [8, 14, 15, 16]. For example, Ding et al. [17] established an connectivity-based partitioning scheme, which can divide the network into many partitions. Yu et al. [18] proposed a coverage guaranteed algorithm, which can divide the network into some domatic partitions. Zhang et al. [19] focused on employing different coverage guaranteed scheduling strategies, which discuss the strategies on different area, such as the border sensors and internal sensors. In order to prolong the network lifetime, CDS concept is utilized to create a virtual backbone in a network [11] [13]. However, these approaches are not consider spatial correlation.

Yuan et al [20] proposed an optimized clustering technique based on spatial-correlation in WSN. Feng et al. [21] propose the sensors' fault diagnosis method base on the data's spatial correlation. Wu et al. [22] studied the optimum sensor density for one- and two-dimensional WSNs with spatial source correlation. Base on the mutual information, Fan et al. [23] proposed a evaluate method for the sensor's transmission behavior. Gong et al. [24] suggested an optimized intermittent transmission method to overcome the information deterioration problem. Das et al. [25] proposed a spatial correlation model for estimating the event-monitoring sensors set size. Jellali et al. [26] propose the sparse representation of the considered signal.

3. Problem Statement and Preliminaries.

3.1. Sensing Coverage Model.

Sensors are always distributed randomly in the application scenarios, for simplicity, their transmission range are set the same. The edges in the network are defined as bidirectional link. Then the WSN is modeled as a graph $G = (V, E)$, where V represent the node set and E represent the edge set, respectively.

A larger number of sensors are distributed into the monitoring area. Thus, if one event happened in the monitor area, several sensors may receive the information at the same time. Since those different sensors monitor the same event, the spatial correlation must exist between them. That is, the relativity about the same event exists among those approaching sensors.

Definition 1. Effective Coverage Rate: The effective coverage rate is defined as the rate between the effective coverage area and the sum of N sensor sensing disk area.

$$R_e = \frac{S_{effective\ coverage\ area}}{N \times \pi R^2}. \tag{1}$$

Then, the coverage weight is defined as $W_{cov} = \frac{R_e * N \times \pi R^2}{S_{area}}$, where S_{area} is the area of monitor location. Especially, $W_{cov}(n_0) = \frac{S_{overlap\ area}}{\pi R^2}$ is the coverage weight of one node.

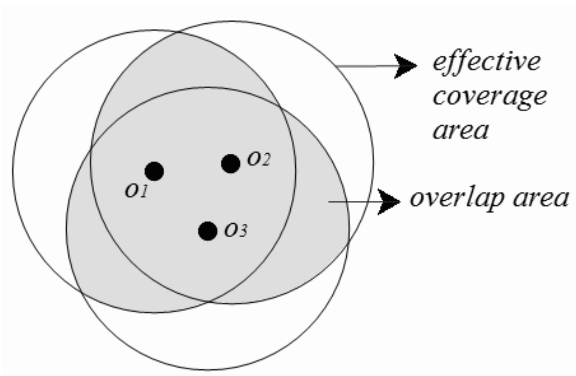


FIGURE 1. One example of the effective coverage rate

The the real network, the overlap of sensing area by two or more sensors is quite high. As shown in Fig. 1, the proportion of the overlap area is high, which will reduce the effective coverage rate. Without overlap area, the effective coverage rate is 100%.

3.2. Cluster Model.

Connected Dominating Set (CDS) is utilized as the method for constructing VB [11]. The nodes selected into a CDS are defined as the dominators. Those adjacent to a dominator are defined as the dominatees. Those dominator nodes constitute a CDS. The dominatees nodes always forward information to the dominator node through the CDS to the sink. Then the information will be forwarded in the CDS, which can reduce the forwarding latency. Next, a spatial correlated CDS construction should be studied as following.

Definition 2. Clique [28]**:** For one graph $G = (V, E)$, a clique S is a complete subgraph, that is to say, there are edges exist between every pair of nodes. k-clique means the clique size is k.

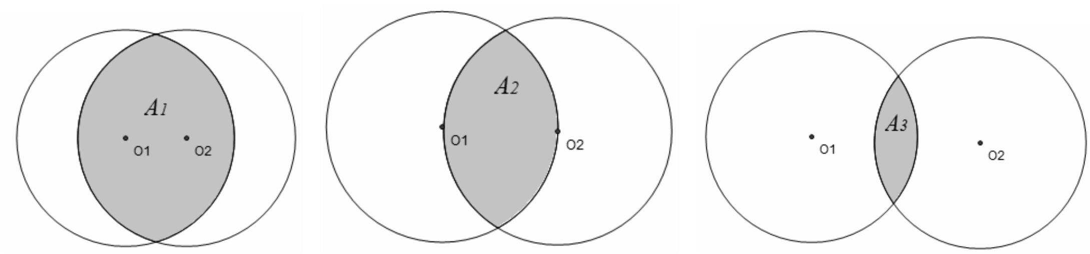
According to the concept of Clique and the Independent Set, we can analyze the Theorems 1 and 2 as following:

Theorem 1. The nodes in the same clique have higher spatial correlation than others.

proof: Three kinds of overlap area may be exist between two circles, which are shown in Figs. 2(a)- 2(c). It is easy to see that the first one (Fig. 2(a)) can obtain the highest spatial correlation. According to Definition 6, sensors are connected in one clique. If two sensors can not exchange messages, the probability of overlap may be low, which is similar to the third one (Fig. 2(c)). The limit condition of two sensors communicating with each other is shown in Fig. 2(b). The area of the shaded part is

$$S_A = 2r^2 arccos(\frac{d_{o_1o_2}}{2r}) - d_{o_1o_2}\sqrt{r^2 - (\frac{d_{o_1o_2}}{2})^2}, \tag{2}$$

where r is the sensing radius, and $d_{o_1o_2}$ is the distance between sensors o_1 and o_2.



(a) overlap A_1 (b) overlap A_2 (c) overlap A_3

FIGURE 2. Overlap

The area in Fig. 2(a) is larger than others, so the nodes in the same clique have high spatial correlation than other nodes. ■

Theorem 2. The set S is a clique of the graph G if and only if S is the maximal independent set of the complement graph $\overline{G}$. Furthermore, S is the maximal independent set if and only if S is the maximal clique of the complement graph $\overline{G}$.

proof: Assuming a simple graph $G = (V, E)$, where $V = 1, 2, ..., n$, the complement graph of G is $\overline{G} =< V, \overline{E} >$, where the nodes v_i and v_j is adjacent in $\overline{G}$ if and only if they are not adjacent in G. Then the problem of finding the maximal independent set of graph G can be transformed into the problem of finding the maximal clique of graph $\overline{G}$. ■

In order to reduce the energy consumption, sensors switch their states between active and sleep. According to the dynamic surroundings and temporal correlation, one sensor can estimate the sleep duration. Based on this parameter, it can adapt several kind of applications.

Topological control is a basic method for maintaining the network performance, furthermore, it is a good method to reduce interference and decrease packet retransmission. Clustering is one of the best topological control methods. With a great cluster algorithm, sensors in the network can be divided into several partitions. Furthermore, the connection also should be guaranteed by adding some sensors into the partitions. The Connected Domatic Partition (CDP) can satisfy this necessary. A CDP of a graph $G = (V, E)$ is a partition $CP_1 \cup CP_2 \cup ... \cup CP_t = V$ of the nodes V such that each set CP_i is a CDS [29]. The partial Connected Domatic Partition is defined as pCP_i.

4. **Spatial Correlation Based Partial Coverage Scheduling Scheme.** In this section, Spatial Correlation Based Partial Coverage Scheduling Scheme (SCCS) is proposed to find the larger size partial coverage dominating partition of graph G. The main idea is to select several spatial correlation based partial coverage CDSs (pCDS) as a backbone network. Each pCDS actives rotation. Then, if partial coverage is not satisfied, additional sensors are selected and activated. The algorithm includes three phases:

First phase: CDS construction, which is the Clique based CDS Construction Algorithm (CCCA).

Second phase: $pCDP$ construction, which guarantees the connectivity and partial coverage by determining the Domatic Partition of a graph. If one partition pCP_i passes the coverage eligibility test and the connectivity test, the sensing area of the partition is covered by some other sensors, and the sensors in the pCP_i are connected. For the sensors that are not selected into the pCP_i, their radio will be turned off.

Third phase: duty-cycling partial coverage based sleep scheduling. Since the CCCA is implemented in each local cluster, the sleep scheduling scheme is a distributed operation.

4.1. **First phase: CDS construction algorithm.** In WSNs, sensors may be clustered to form a hierarchical topology in order to reach energy efficiency and scalability. Sensors can send their sensing data to a cluster-head, the one in the CDS, which in turn aggregates and forwards the data to the sink. In this paper, according to Theorems 1 and 2, the CDS constructed algorithm is based on the clique. Some assumptions are made as follows:

Since those connected sensors have high spatial correlation, the method of complement graph and clique will be employed in this section for the clustering algorithm. When the two neighbours are not adjoined in the local complement graph $\overline{G}$, they will be colored with different colors. On the contrary, the sensors can be colored with the same color if they are adjoined in the clique. Then a clique construction S in $\overline{G}$ is corresponding to one kind of color in G. For $\forall x \in V \backslash S$, at least one CDS sensor x can be found in S. As this is a distributed algorithm, the global information do not necessary, just one hop information is needed. Furthermore, in order to execute the algorithm asynchronously, a countdown $Time$ is set, which is calculated as Eq. (3).

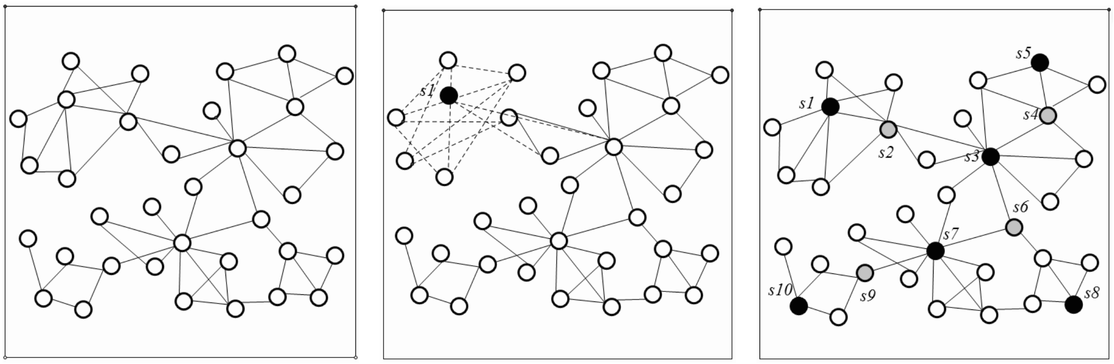
$$T = \frac{random(ID)}{c_1 W_{cov}(n_0) + c_2 R_n} \tag{3}$$

where ID denotes the sensor's identity number, $W_{cov}^{n_0}$ denotes the cover weight of the sensors, R_n denotes the residual energy, c_1 and $c_2$denote the weight factors that satisfies $c_1 + c_2 = 1$. That is, Eq. (3) not only guarantees that each sensor has different countdown $Time$, but also consider the factors of cover weight and energy. The higher the cover weight is, the larger overlap area and the higher spatial correlation are. Alg. 1 describes the Clique based CDS Construction Algorithm.

An example are shown in Figs. 3(a)- 3(c). Fig. 3(a) is the original graph, Fig. 3(b) shows that the sensor $s1$ is selected in the CDS, and colored with color 1. The dotted line means that the conjoint sensors are contained in the complement graph.

When the new complement graph need to be constructed, two cases will be occurred: firstly, there are sensors which are adjoin to the last center, if there are only one sensor, this sensor can be chosen as the new center, and colored with color 1, if there are more than one sensors, the countdown time started, whose T die first can be chosen as the new center and colored with color 1, then return to line 03 in Alg.1; Secondly, there is no sensor

Algorithm 1: Clique based CDS Construction Algorithm (CCCA)
01: begin
02: Select some initializers randomly;
03: Construct one hop complement graph (initializer as the center);
04: The lowest degree node is select (colored 1);
05: Start each one hop neighbours' countdown time T;
06: Select whose time die first as the center (colored 2);
07: and sent this messages to its neighbours.
08:end



(a) Original network (b) The complement graph with the center $S1$ (c) The backbone network

FIGURE 3. One example of the CCCA

which adjoin to the last center, return to lines 05-07 in Alg. 1. The sensors which are colored with color 2 are as the connected sensors. After implementation of the algorithm, the sensors $s1, s3, s5, s7, s8$ *and* $s10$ are selected as the CDS, and $s2, s3, s6$ *and* $s9$ are the connected sensors, which are shown in Fig. 3(c).

In the distributed algorithm, several initiators are selected in the whole network, which can make the CDS construction more effective. However, the conflict will happen when two subnets meet each other as execute the algorithm. So the algorithm should be executed to avoid the collision.

(1) When one initiator broadcasts the algorithm start message, at the same time, it receives the same kind of message from its neighbors. That is, two adjoin sensors want to be the cluster head. Then, the countdown timer start, whose time is died first will be the initiator.

(2) When two subnets meet at one sensor, then three possible scenario will be carried out. Case one: the subnet 1 execute line 03 in Alg.1, and one sensor becomes a center's neighbor; case two: the subnet 2 execute lines 05-07 in Alg. 1, the sensor becomes the center; case three: subnet 3 execute line 03 in Alg.1, and the sensor is adjoin one cluster head in the complement graph.

When the conflict of cases one and two happen, the subnet 1 stops executing the algorithm. If the conflict of cases one and three or the case two and three happen, the algorithm will finish at these three subnets. At the same time, this sensor is colored with color 2 and becomes the connector.

4.2. **Second phase:** $pCDP$ **Construction.** The sensor coverage problem is important and can be divided into 3 kinds: area coverage, point coverage and barrier coverage. The area coverage problem is used in this section. Then, an efficient coverage intensity is proposed. The model studies two problems: 1) Expected coverage ratio with CDP algorithm and 2) Spatial correlation based scheduling strategy with planned scheduling.

According to Formula (1), each cluster's coverage value can be calculated. If the network aims to trace some events, the whole coverage is not necessary. Assume that the partial coverage value is determined by the events, a partial coverage threshold η can be set according to the events, which is not the key issue in this paper. If $W_{Cov}(u)$ is greater than a given partial coverage threshold η, only one sensor with high coverage value the highest energy can be active. Otherwise, more than one sensor will be waked in a cluster.

Each CDP will be constructed according to the available information, then the coverage by the CDP is higher than partial threshold η. With partial coverage $pCDP$ algorithm, all sensors are divided into t partitions. However, the partition algorithm cannot ensure that each partition is interconnected. So, we need to add some sensors into the partitions, in order to make sure that each partition is connected.

For the partial coverage threshold η, the spatial correlation based event detection algorithm will be proposed. The event i is defined as $Inf(i) = \{time, local, \delta\}$, where $time$ is when the event happen, $local$ is where the event happen, and δ is the spatial correlation threshold. Then, the spatial similarity need to be calculated. If at one time, the data sequences of some neighbors are quite different from that of before, and satisfy some kind of spatial similarity degree, that is to say some events may happen in this location. The spatial similarity is calculated as

$$q(x_t, y_t) = \frac{1}{1 + \sqrt{\sum_{k=1}^{d} (x_k^t - y_k^t)^2}}, \tag{4}$$

where $q(x_t, y_t)$ is the spatial similarity, x_t, y_t is the location of sensor n_t, d is the number of the neighborhood of sensor n_t. If $q(x_t, y_t) \geq \delta$, the area of the location will be calculated into the η, which can be calculated as

$$\eta = \frac{\bigcup\{local_i\}}{A_{area}}. \tag{5}$$

4.3. **Third phase: scheduling algorithm.** After executing algorithm 2, many partial coverage CDPs can be constructed. At each time slot, one pCDS is used as the backbone. In other words, duty-cycling has become an integral technique for WSNs. Partial coverage DP combines each partition with duty-cycling by letting backbone sensors work in a duty-cycled fashion, which is called the Spatial Correlation Based Partial Coverage Scheduling Scheme (SCCS).

Assume there are t clusters $pCP = \{pCP_1, pCP_2, ..., pCP_t\}$ have been selected. At first, set t=current-time, schedule time for $pCP_i \leftarrow t + i \times \tau_{pCP_i}$ and then switch from pCP_i to pCP_j. At the beginning of each round, if the active sensors selected by the previous round cannot pass the coverage and connectivity check, these sensors will go into the sleep mode. If the sensors selected into the pCP_i in this round as active mode.

5. **Simulation.** A comprehensive performance evaluation is proposed in this section. At first, the implementation of the methods we choose as a comparison will be presented in detail. Then we present experimental results obtained through simulation, showing that SCCS performs better than other existing schemes.

The simulation is used to estimate the performance of SCCS using JAVA for programming. 500 sensors are spread in the $1000 * 1000$ network simulation area randomly. Fig. 4 shows the examples of the algorithm with the partial coverage $\eta = 100\%$. After operate

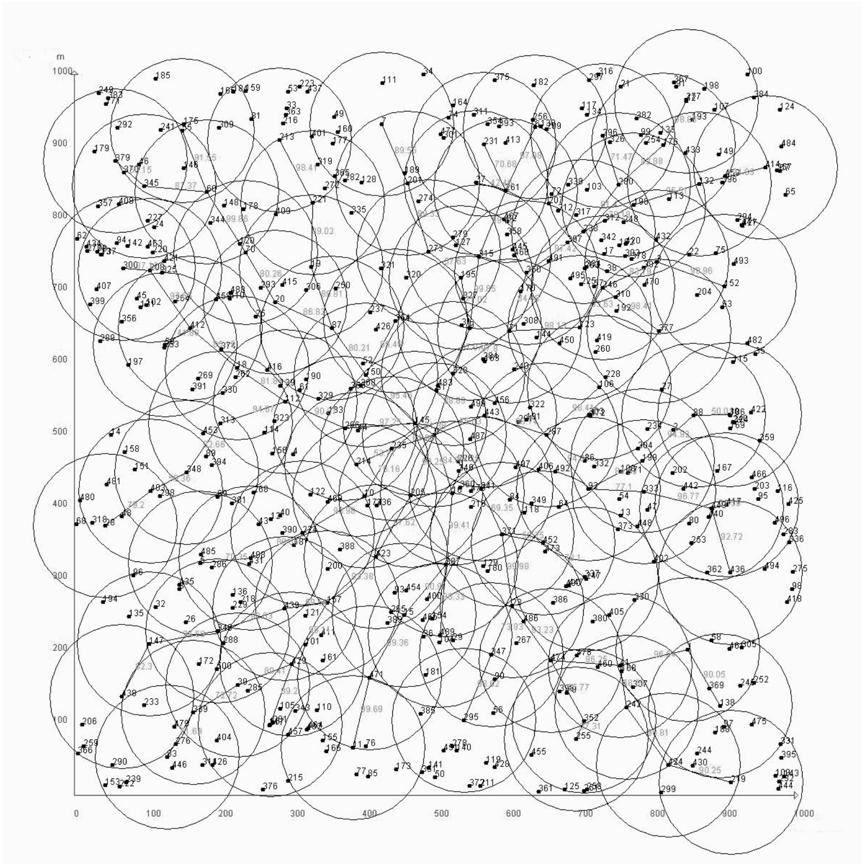
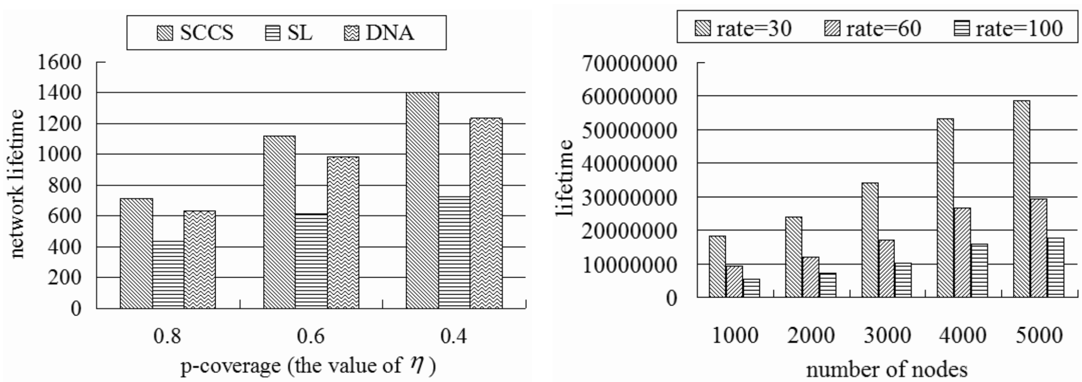


FIGURE 4. The connected dominating set

the SCCS, the virtual backbone is constructed in Fig. 4, which can satisfy the 100% coverage and connectivity. About 30 cluster head will be selected into the CDS. It is a low rate comparing to the number of the sensors, which are deployed in the network.



(a) The network lifetime is different when different amount of information needs to be transmitted.

(b) The network lifetime of different algorithms with different thresholds.

FIGURE 5. The network lifetime comparison

Then, we show the network sensing p-coverage η versus the lifetime for the SCCS. Assume that 500 sensors are deployed in the area. Fig. 5(a) gives the achieved network lifetime by different algorithms, it is compared to the topology-based Smallest Last vertex deletion (SL) algorithm [13] and the Distributed Nucleus Algorithm (DNA) [18]. It is easy to see that whatever η is, SCCS has better performance for prolong the network's lifetime. On the other hand, the network lifetime will be effect by the forwarding rate of the sensors. The rate are set from 30% to 100%. As shown in Fig. 5(b), since more information need to be forward, more energy will be consumed. Then there is the higher the forwarding rate is, the shorter the lifetime is.

6. **Conclusions.** Wireless Sensor Networks is widely used, especially for the environmental monitoring. However, since the sensors are resources limited, energy saving and lifetime prolonging become more and more important. In this paper, we focus on the spatial correlation based virtual backbone construction for the target monitoring and propose an efficient algorithm that relies on the Construct Dominating Set. By minimizing the number of sensors to activate, we propose a Spatial Correlation based partial Coverage Scheduling Scheme (SCCS) to prolong the network lifetime. The experimental indicate the efficiency and feasibility of the SCCS.

For the future research direction, firstly, we will focus on data prediction which can help us locate the position that have much data need to be forward. Then a data prediction based scheme will be discussed in the future. Furthermore, secure data aggregation management will be considered as there are many security threats in the network.

Acknowledgment. The authors wish to thank National Natural Science Foundation of China (Grant No.: 61902069), Natural Science Foundation of Fujian Province of China (2017J05098, 2018J01619) and Fujian Provincial key project(2017H0001).

REFERENCES

[1] M. Dong, K. Ota, A. Liu, and M. Guo, Joint Optimization of Lifetime and Transport Delay under Reliability Constraint Wireless Sensor Networks, *IEEE Transactions on parallel and distributed systems*, vol.27, no.1, pp.225–236, 2016.

[2] H. Mostafaei, A. Montieri, V. Persico, and A. Pescap, A sleep scheduling approach based on learning automata for wsn partial coverage, *Journal of Network and Computer Applications,*vol.80, no.C, pp.67–78, 2017.

[3] J. S. Pan, L. Kong, T. Sung, S. Chu and J. F. Roddick, Hierarchical Routing Strategy for Wireless Sensor Network, *Journal of Information Hiding and Multimedia Signal Processing*, vol.9, no.1, pp.256–264, 2018.

[4] J. S. Pan, T. T. Nguyen, T. K. Dao, T. S. Pan, and S. Chu, Clustering Formation in Wireless Sensor Networks: A Survey, *Journal of Network Intelligence*, vol.2, no.4, pp.287–309, 2017.

[5] Y. Huang and C. Hsu, Energy Efficiency of Dynamically Distributed Clustering Routing for Naturally Scattering Wireless Sensor Networks, *Journal of Network Intelligence*, vol.3, no.1, pp.50–57, 2018.

[6] L. Kong, J. S. Pan, V. Snasel, P. Tsai, T. Sung, An energy-aware routing protocol for wireless sensor network based on genetic algorithm, *Telecommunication Systems*, vol.67, no.3, pp.451–463, 2018.

[7] J. Zhang , S.J. Liu, P.W. Tsai, F.M. Zou, and X.R. Ji, Directional virtual backbone based data aggregation scheme for wireless visual sensor networks, *PloS one,* vol.13, no.5, e0196705, 2018.

[8] J. Zhang, L. Xu, P. W.Tsai,, and Z. Lin, Minimization of delay and collision with cross cube spanning tree in wireless sensor networks, *Wireless Networks,* vol.25, no.4, pp.1875–1893, 2019.

[9] B. Gong, P. Cheng, Z. Chen, N. Liu, L. Gui, and F.D. Hoog, Spatiotemporal compressive network coding for energy-efficient distributed data storage in wireless sensor networks, *IEEE Communications Letters,* vol.19, no.5, pp.803–806, 2015.

[10] C.F. Cheng, and C.W. Wang, The target-barrier coverage problem in wireless sensor networks, *IEEE Transactions on Mobile Computing,* vol.17, pp.1216–1232, 2018.

[11] J. Zhang, L. Xu, S. Zhou, G. Min, Y. Xiang, and J. Hu, Crossed cube ring: a k-connected virtual backbone for wireless sensor networks, *Journal of Network and Computer Applications,* vol.91, pp.75–88, 2017.

[12] J. S. Pan, L. Kong, T. Sung, P. Tsai, V. Snasel, A Clustering Scheme for Wireless Sensor Networks Based on Genetic Algorithm and Dominating Set, *Journal of Internet Technology*, vol.19, no.4, pp.1111-1118, 2018.

[13] D. Mahjoub, D.W. Matula, Employing (1 -ε) dominating set partitions as backbones in wireless sensor networks, *Meeting on Algorithm Engineering and Expermiments, Society for Industrial and Applied Mathematics,* vol.2010, pp.98–112, 2010.

[14] J. Zhang, L. Xu, S. Zhou, and X. Ye, A novel sleep scheduling scheme in green wireless sensor networks, *Journal of Supercomputing,* vol.71, no.3, pp.1067–1094, 2015.

[15] G. Nan, G. Shi, Z. Mao, and M. Li, Cdsws: coverage-guaranteed distributed sleep/wake scheduling for wireless sensor networks, *Eurasip Journal on Wireless Communications and Networking*, vol.2012, no.1, pp.44, 2012.

[16] C. Liu, K. Wu, Y. Xiao, and B. Sun, Random coverage with guaranteed connectivity: joint scheduling for wireless sensor networks, *IEEE Transactions on Parallel and Distributed Systems,* vol.17, no.6, pp.562–575, 2006.

[17] Y. Ding, C. Wang, and L. Xiao, An Adaptive Partitioning Scheme for Sleep Scheduling and Topology Control in Wireless Sensor Networks, *IEEE Transactions on Parallel and Distributed Systems*, vol.20, no.9, pp.1352–1365, 2009.

[18] J. Yu, Q. Zhang, D. Yu, C. Chen, and G. Wang, Domatic partition in homogeneous wireless sensor networks, *Journal of Network and Computer Applications,* vol.37, pp.186–193, 2014.

[19] D.Q. Zhang, D. Li, High-Density Randomly Deployed Nodes Sleep Scheduling Algorithm in Wireless Sensor Networks, *Advanced Materials Research,* vol.846, pp.446–451, 2013.

[20] J. Yuan, H. Chen, The optimized clustering technique based on spatial-correlation in wireless sensor networks, *IEEE Youth Conference on Information, Computing and Telecommunication,* vol.2009, pp.411–414, 2009.

[21] Y.B. Feng, R.B. Zhang, Fault Detection of WSN Based on Spatial Correlation, *Applied Mechanics and Materials,* vol.58, no.60, pp.1504–1510, 2011.

[22] J. Wu, N. Sun, Optimum Sensor Density in Distortion-Tolerant Wireless Sensor Networks, *IEEE Transactions on Wireless Communications,* vol.11, no.6, pp.2056–2064, 2012.

[23] X. Fan, H. Okada, K. Kobayashi, and M. Katayama, Mutual information evaluation and optimization of intermittent transmission methods in energy harvesting wireless sensor networks, *Ieice Trans Commun,* vol.97, no.9, pp.1826–1834, 2014.

[24] B. Gong, P. Cheng, Z. Chen, N. Liu, L. Gui, and F.D. Hoog, Spatiotemporal compressive network coding for energy-efficient distributed data storage in wireless sensor networks, *IEEE Communications Letters,* vol.19, no.5, pp.803–806, 2015.

[25] S.N. Das, S. Misra, B.E. Wolfinger, and M.S. Obaidat, Temporal-correlation-aware dynamic self-management of wireless sensor networks, *IEEE Transactions on Industrial Informatics,* vol.12, no.6, pp.2127–2138, 2016.

[26] Z. Jellali, L.N. Atallah, S. Cherif, Data acquisition by 2D compression and 1D reconstruction techniques for WSN spatially correlated data, *Proc. of International Symposium on Signal, Image, Video and Communications, IEEE,* pp.224–229. 2017.

[27] V. Akbarzadeh, C. Gagne, M. Parizeau, M. Argany, and M.A. Mostafavi, Probabilistic sensing model for sensor placement optimization based on line-of-sight coverage, *IEEE Transactions on Instrumentation and Measurement,* vol.62, no.2, pp.293–303, 2013.

[28] X. Wen, W.N. Chen, Y.Lin, T. Gu, H. Zhang, and Y. Li, Y. Yin and J. Zhang, A maximal clique based multi-objective evolutionary algorithm for overlapping community detection, *IEEE Transactions on Evolutionary Computation,* vol.21, no.2, pp.363–376, 2017.

[29] J. Zhang, L. Xu, W. Wu, H. Yang, Virtual Backbone Scheduling with Connected Domatic Partition in Wireless Sensor Networks, *ad hoc and sensor wireless networks,* vol.38, pp.169–198, 2017.