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Wireless Sensor Network Topology Control Based on Agent

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Abstract: Based on multi-Agent and learning-reinforcement adaptive topology control algorithm of wireless sensor network, this paper abstracts the wireless sensor network topology control into multi-Agent and global-coordination optimization problem on the basis of payment and localizes the global evaluation function by taking advantage of SparseQ in order to form effective topological structure and optimized data forwarding path in random deployment mode. This paper also probes into forming initial topological structure and data forwarding path by the interaction of detection information and return information among local Agents, and probes into ensuring topology's continual updating and optimization by the renovation of return information and path selection evaluation values in the process of data forwarding. The simulation shows that the algorithm improves the data transmission quality and energy efficiency in the specific application of wireless sensor network in random deployment mode. *Copyright © 2013 IFSA.*

Keywords: Wireless sensor networks, Agent, Mobile agent, Multi-agent system, Topology control, Multi-agent reinforcement learning.

1. Introduction

Wireless sensor network is a wireless, self-organizing, fault-tolerant, dynamic, application-related, and data-centric new information network[1], which can collaborate to monitor, perceive and process all kinds of information in the coverage area of network, so that we can extend to the broader interactive space and achieve more precise and profound understanding and controlling of the external world. So in the fields of military, environment, health, industry, agriculture, commerce, disaster rescue, space exploration, family, traffic, safety and facility management it has broad application prospects, and also has revolutionary impact on people's life and work mode, industrial development and reform[2].

In the development of the existing network technology, low-power radio communication technology, distributed information processing technology, embedded computing technology, micro-sensor technology and integrated circuit technology wireless sensor network shows its advantages of small node, fast large-scale deployment, unattended, and also shows its disadvantages of limited energy supply, communication capability, computing and storage capacity [3]. Therefore, it is necessary to have a reasonable design and control of wireless sensor networks and applications system for improving the operational efficiency and reliability, and completing the set application target to make the

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entire network run more economically. But the problems the wireless sensor network encounters are different from those of other existing information network so it needs models and methods that fit its characteristics.

Wireless sensor network is a self-organized network with sensor nodes through wireless. These senor nodes usually have functions of sensing, processing and wireless communication. In the management of wireless sensor network, topology management is generally through power control and hierarchical topology control under the premise of meeting the network coverage and connectivity, then forming an optimized network structure of data forwarding [4]. In the aspect of power control, many algorithms have been proposed such as COMPOW, LINT/LILT, LMN/LMA, CBTC, LMST, RNG, DRNG and DLSS, etc. [5]. In the hierarchical topology control, people have proposed algorithms such as TopDisc, GAF, LEACH, HEED, etc. [6]. The topological structure of wireless sensor network can be divided into planar structure and hierarchy structure [7]. The generation and control algorithms in the typical planar structure have ASCENT, SPAN, STEM, etc. [8], but the disadvantages of planar structure network are no management node in the network, the algorithmic complexity of self-organizing collaborative work, and the slow response in the dynamic network. REMUDA [9] is the topology control in wireless sensor network and data forwarding mechanism, which is used in the indoor parking management system, and it forms a tree-based hierarchical network topology, as far as possible more nodes as leaf nodes and build a virtual cluster structure, while still in the process of building the tree taking into account reliability, stability and path length and other factors. Liu and Haenggi proposed a topology control algorithm for quasiregular sensor network [10] to improve the energy efficiency and life cycle in this network. Corresponding to the planar structure is a hierarchy structure, it is the complex of a central structure and no central structure, generally exist in the form of clusters [11], has the characteristics of good expansibility, convenient management etc. The current topology management in wireless sensor network mainly considers the efficient use of energy, also need to do in-depth research in the aspects of robustness, fault tolerance and topology information control etc.

Wireless sensor network is different from the traditional network (such as LAN, Internet, mobile communication network and the packet data network, etc.) in characteristics and design requirements. In specific applications, many factors, for instance, the self-organizational requirements and limited resources, possibly irregular deployment in complex application environments, node mobility or failures and dynamic wireless intermittent connection, and numbers of uncontrolled edge network topology, lead to complicated and inefficient wireless sensor network data forwarding path, waste of node resources, reduce the throughput and life cycle of the network. Therefore, it is necessary to study the problem of topology control in the wireless sensor networks, establish an effective topology, reduce energy consumption and network congestion, and improve overall performance of the network and the spatial reuse in the wireless communication.

This paper based on the existing researches and combines with the features and applications in the wireless sensor networks, uses the theories and methods of multi-agent reinforcement learning, studies adaptive wireless sensor network topology control algorithm in the random deployment of wireless sensor networks, establishes theoretical model in the wireless sensor networks and collaboration logic based on Agent and Multi-Agent system, discusses the mechanism of self-organization, and builds an adaptive topology control method based on multi-Agent. Investigating the problems in wireless sensor networks by existing theories and researches on Agent and Multi-Agent system will contribute to modeling and analysis the essential characteristics at a higher level, in order to further solve the problem, conflicts and contradictions under a variety of collaborative strategies and programs, finally achieve the collaboration and autonomy in the wireless sensor network system.

2. The Topology Model of Multi-Agent Systems in Wireless Sensor Network

Wireless sensor network is a self-organizing, dynamic, data-centric, application-related system, each node is able to automatically forward monitoring data through the topology control mechanism and network protocol, from the identified domain and boundaries of system, a well-designed node is an autonomous behavior Agent, which is independent and consistent with the design goals. The entire network is a multi-Agent system [12]. In the wireless sensor networks, corresponding to a different applications, network protocols and algorithms as well as the individual's ability each Agent establishes its relevant world model and its reasoning.

Through itself and interaction with other nodes, each node after deployment makes its behavior under certain circumstances. In the wireless sensor network, each Agent will establish its world's internal model for functioning in a change world. Corresponding to different applications, network protocols and algorithms and the ability of individuals, some of the Agent can clearly establish its world model and reasoning for the relevant model; while other Agent models may contact with the hardware and be distributed throughout the network architecture. The Agent in the wireless sensor network can be regarded containing four parts, which are internal state, control logic, sensors and actuators. It is shown in Fig. 1.

We defined the Multi-Agent System Mode of the wireless sensor network as a collaboration diagram [13] G = (V, E), each node represents an Agent, each edge represents the connection and cooperative relations between Agent i and an Agent j, and an Agent i depends only on a set of Agent, the Interactive process between Agents in the completion of the stated objectives is a collaborative Multi-agent MDP (CM-MDP).

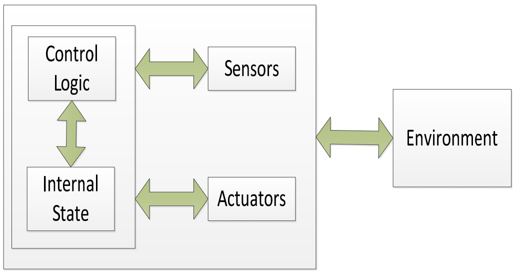

Fig. 1. Agent architecture of wireless sensor network node.

CM-MDP [14] is the extension of MDP: t = 0, 1, 2...., discrete-time: $A = \{A_1, A_2, \dots\dots, A_n\}$ is a finite set of Agent; S_i is the set of discrete state variables.

$$S = S_1 \times S_2 \times \dots\dots \times S_m, S^t \in S \tag{1}$$

CM-MDP describes the state of the world model at time t, A_i is the availability action set for the i-th Agent, $a_i^t \in A_i$ is the chosen action of i-th Agent at time t, $a^t \in A = A_1 \times A_2 \times \dots\dots \times A_n$ is the combination of all individuals actions of n Agent at time t ; $T: S \times A \times S \rightarrow [0,1]$ is a state transforming function, which means that in the state $S^t \in S$ the Multi-Agent takes joint action to transfer into state S^{t+1} with probability $p(s^{t+1}|s^t, a^t)$; $R_i: S \times A \rightarrow R$ is reward function, which means that in the status $S^t \in S$ it gives the i-th Agent return $r_i^t \in R_i(s^t, a^t)$ when taking joint action a^t, overall returns is the sum of all the individuals Agent returns。

$$R(s^t, a^t) = \sum_{i=1}^{n} R_i(s^t, a^t) \tag{2}$$

Strategy $\pi: s \rightarrow a$ is the function which returns an action A for the given state.

In a dynamic application environment, with its autonomous control and transmission capacity, each Agent has its behavior met the design goals and the information it carries got shared, collaborated and merged in G. When one of the Agents fails, the information can guarantee the stability of the network topology. The objectives of wireless sensor network topology control Based on Multi-Agent System Model are learning and evaluating Agent connectivity, eventually forming a highly efficient topology model, before that one has to graphical map for cooperative relationship between Agents based on local interactive information related to topology in G. An Agent can learn associated connectivity information and realize the system map by traversing a part of or the entire network with adjusting the power. If resources, especially energy, efficiency considered, the power must be controlled. One effective method is sharing their mapping information on G with a group of agent on which it relies, then resource usage can be reduced, finally stated objectives will be accomplished by collaborate. The performance of Multi-Agent Collaborative Systems in the Wireless sensor network does not only rely on a single Agent operational efficiency, but also on how all Agents exchange information with each other and use them in general, conduct proper divisions of work to achieve effective collaboration, and achieve the global benefit maximizing.

3. The Collaboration with Multi-Agent Reinforcement Learning

In the machine learning, Agent Reinforcement Learning aims to enable the Agent sense the environment by learning to choose the optimal action for completing the target [15]. For CM-MDP, The Collaboration with multi-Agent Reinforcement Learning objectives [16] is to find an optimal policy π^*, so that for each state s, the value of future cumulative expected returns.

$$V^*(s) = \\ = \max_\pi E[\sum_{k=0}^{\infty} \gamma^t R(s^t, \pi(s^t)) | \pi, s^0 = s] \tag{3}$$

Its value is the maximum, which is discount factor, when multiple Agent select a specific action and optimize the operation, you can use the Q function or action - valued function to represent the value of future cumulative return in a given state

$$Q^*(s,a) = R(s,a) \\ +\gamma \sum_{s'} p(s'|s,a) max_{\partial'} Q^*(s',a') \tag{4}$$

Given Q^*, in the state of S, the Agent optimal strategy is the joint choice of maximizing future cumulative return value arg $max_\partial Q^*(s,a)$.

In the process of the completing the stated objectives, the work of Multi-Agent Reinforcement Learning is to estimate $Q^*(s,a)$, the widely used method is Q-learning [17], each state - action pair has an assessed value of the initial Q, each Agent select an action based on certain search strategy, when in the states it performs an action a, to obtain a return R (s, a), then transfers to the state s', the corresponding evaluation value Q can be updated as follows [18]:

$$Q(s,a) = (1-\alpha)Q(s,a) \\ + \alpha[R(s,a) \\ + max_{a'} Q(s',a')], \alpha \\ \in (0,1) \tag{5}$$

It is learning control parameters. Taking into account the characteristics of self-organization, limited resources, the complexity of application conditions and the wireless intermittent connection in the dynamic network, wireless sensor networks is difficult to directly update the global $\mathrm{Q(s,a)}$ using of formula 3, therefore, this chapter uses sparse cooperative Q learning methods (Sparse Cooperative Q-1earning, or Sparse Q) [19] to decompose the global $\mathrm{Q(s,a)}$ into a linear combination of local Q function.

Taking into account of the CM-MDP $\mathrm{Q(s,a)} = \sum_{i=1}^{n} Q_i(s_i, a_i)$ and the VE (Variable Elimination) algorithm [20], it determines the joint action $a^* = \arg max_{a'} Q^*(s', a')$ in the optimal state, then calculates the contribution $Q_i(s_i', a_i^*)$ for each Agent on the assessed value $\mathrm{Q}(s', a^*)$ of the entire action, gets Agent i's local update function:

$$Q_i(s_i, a_i) \coloneqq (1 - \alpha) Q_i(s_i, a_i) + \alpha [R_i(s, a) + \gamma Q_i(s_i', a_i^*)] \tag{6}$$

4. Topology Control Algorithm Based on Collaborative Multi-Agent Reinforcement Learning for Wireless Sensor Network

Let wireless sensor network has N +1 nodes, number of convergence nodes is 1 (identified as 0), number of common nodes is N (identified as 1,..., N), the maximum hop count in the wireless communication is M between the common node and the sink nodes; Energy of the i-th Agent is $e^{(i)}$ (maximum energy E_{max}, energy $E_{current}^{(i)}$ is present, then $e^{(i)} = \frac{E_{current}^{(i)}}{E_{max}}, 0 \le e^{(i)} \le 1$), the quality of the wireless communication between Agent i and Agent j (taking) is $w^{(i,j)}, 0 \le w^{(i,j)} \le 1$,. Each Agent table entry for "return value" (R, set maximum return value R_{max}), the "minimum hops" (h), "state - action-Q assessed value", the state correlated with the time.

The G = (V, E) formula is given as a Multi-Agent System Model in the wireless sensor network, In the CM-MDP, one Agent action is to select one or more Agent from N Agents as destination nodes in the data transmission, Here for sink nodes possible targets of data transmission include all ordinary nodes, while for the ordinary nodes the possible targets of data transmission are other N Agents except itself(sink nodes included).Given Agent i, the action set Λ_i , which contains N elements, each Agent i from the action set Λ_i to choose a single action a_i will be paid $f_i(a_i)$, in this algorithm, take $f_i(a_i)$ as Q assessed value for corresponding actions a_i , joint action in the entire network is a = $(a_1, \dots \dots, a_N)$, the global payment function $\mathrm{u(a)} = \sum_{i=1}^{N} f_i(a_i)$. The algorithm to solve the topology control problem in the wireless sensor network is to find optimal joint action a^* , then maximize u (a), that is $a^* = \arg max_a u(a)$.

4.1. The Formation of Initial Topology

Each Agent (except the sink node) detects information with the same power broadcasting, according to their own resources (energy, computing power and wireless communication capabilities, etc.) each Agent detected information gives a certain return information to the source node, including the node number, the return value; Each Agent receives returned information from other Agent, then according to this information establishes to be selected "state - action-Q assessed value" entries for expected cooperation Agent. In general, the more resources there are, the smaller distance the sink nodes are away from on multiple paths; the larger return value Agent has, the more possible its adjacent Agent will be selected. In the initial topology formation phase, algorithm takes corresponding actions Q assessed value as return values. As a whole network detecting information node, sink node is the ending receiving point, it will give return message which contains maximum return value to neighboring nodes.

The specific algorithm:

Step 1: Each Agent (except the sink nodes) probes information with the same power broadcasting. The detection information includes Agent identification, estimating the parameters of wireless energy, etc. Each Agent receives probed information from other Agent, estimates the wireless energy consumption in Agent and with Agent identifies form a table entry about the transmitted return information.

Step 2: The sink nodes receive detection information from a neighbor Agent, delaying a certain time, start the entire network to send return value;

In this process, Agent i sends a return value to Agent j:

$$R_{\mathrm{ij}}(a_j) = max_{a_i} \{ f_i(a_i) + \sum_{k \epsilon \Gamma(i) \backslash j} R_{ki}(a_i) + c_{ij} \} \tag{7}$$

where $\Gamma(\mathrm{i})\backslash\mathrm{j}$ represent all neighbor nodes of the Agent i, except Agent j, c_{ij} is the normalized value, the return value is for a given action Agent j(i.e. Agent j as the next hop node), Agent i can obtain the approximate value of maximum payment, depends only on payment of dependency between Agent i and Agent j as well as the input information of Agent i. The sink node is usually a well-resourced Agent, $f_0(a_0)$ need to take very large value, its purpose is to send the information across the network path by the sink node-oriented, for $\mathrm{k\epsilon\Gamma(i)\backslash j}$ initially $R_{ki}(a_i) = 0$.

Step 3: form the preliminary optimal path;

Before the initial topology formation the deadline arrives, Agent i repeat the following steps; waiting for other Agent for return information; when received return information from other Agent, Agent i for all the neighbors jϵΓ(i) calculates $R_{ij}(a_j)$,if the difference of $R_{ij}(a_j)$ and previous return information for Agent j exceeds a certain threshold, send the information $R_{ij}(a_j)$ to the Agent j.

4.2. Topology Optimization

In the actual operation, participating in information transmission each Agent will remain reinforcement learning, based on the maximum return given by adjacent Agent, through updating the evaluation value of Q, and then optimize path selection. Due to environmental conditions, energy depletion, changes in the wireless communication link and other factors, Wireless sensor network changes the topology dynamically, so the return value of Agent, which is composed of various parameters, is constantly updated during operation, and feedbacks to the adjacent Agent. Its process ensures the stability of wireless sensor network topology.

In the initial formation of the effective topology, the wireless sensor network begins transmitting information based on the topology, further optimizes the topology and data forwarding path, the specific algorithm is:

When Agent i receives the information from Agent j, at first it evaluates the quality of wireless communication between Agent i and Agent j; then it calculates the return value sending to Agent j, as follows

$$R_{ij} = (\delta_1 \left(1 - \frac{m}{M}\right) + \delta_2 e^{(i)} + \delta_3 w^{(i,j)}) R_{max} \tag{8}$$

Where m is the hop counts between Agent i and the sink node, the weighting coefficient of each parameter,, 0 ≤ m ≤ M, $\delta_i (1 \le i \le 3, \sum_{i=1}^{3} \delta_i = 1)$

When Agent i received the return value from the Agent j

Create or update the "state - action-Q assessed value" entries, where the action is to select Agent j as the next hop node, Q assessed value:

$$Q_i(s_i, a_i) = (1 - \alpha) Q_i(s_i, a_i) + \alpha [R_{ij} + \gamma \sum_{k \epsilon \gamma \backslash j} \frac{Q_k(s_i, a_k)}{|\gamma \backslash j|}] \tag{9}$$

Taking into account of VE algorithm involved the global Agent, large amount of calculation, the algorithm is taking $Q_i(s_i', a_i^*) = \sum_{k \epsilon \gamma \backslash j} \frac{Q_k(s_i, a_k)}{|\gamma \backslash j|}$ in Equation 7, here $\gamma \backslash j$ which is the set related the next hops of candidate Agent except j in the "state - action-Q assessed value" entries.

5. Simulation Analysis

We do simulation experiments on Power TOSSIM [21, 22], all the nodes in a certain period collect data to the aggregation node, the wireless communication uses an experimental model [23, 24],comparing the topology control algorithm based on collaborative Multi-Agent Reinforcement Learning in the wireless sensor network (called MRLTC) with Typical applications Surge Reliable [25] in the wireless sensor networks.

Experiment 1: 200 nodes (including the aggregation node) randomly deploy in a 500 m × 500 m area (Fig. 2). It can study the average packet loss rate and the average number of hops between Surge Reliable and MRLTC in the data transfer stage.

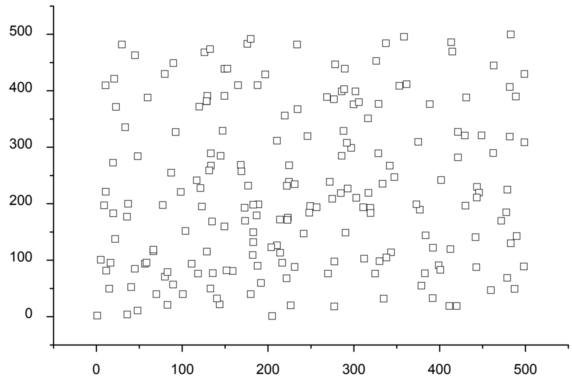

Fig. 2. Scene 1 with 200 nodes in Experiment 1.

The average distance between nodes is assumed as 20 m; The energy of sink node is abundant, the communication distance is 50 meters; the total energy of general nodes is 10 kJ, the communication distance is 30 m, when the residual energy is less than 0.1 % of the total energy, stop operating; taken in formula (7) c_{ij} is 0, the formula (9) α is 0.3, γ is 0.2, δ_1 is 0.5, δ_2 , δ_3 are 0.25 (Table 1). Every 200 ms simulation time each node generates a data packet, in the wireless communication model set for different links with each type of packet loss rate.

Table 1. Simulation parameters.

Parameter type	Parameter value
c_{ij}	0
α	0.3
γ	0.2
δ_1	0.5
δ_2	0.25
δ_3	0.25

Repeat simulation 10 times with 100 s; calculate the average packet loss rate and the average number of hops. It is shown in Figs. 3, 4.

From Fig. 3, the average packet loss rate of MRLTC is higher at the beginning of data transmission than that of Surge Reliable, but with MRLTC network topology gradually optimized, the average packet loss rate of MRLTC reduces gradually compared to Surge Reliable, and it has been maintained fluctuated at a low level. Statistics show that Surge Reliable has an average packet loss rate of 7.2786 % in 100 s of simulation time, while MRLTV has a rate of 5.364 %.

From Fig. 4, MRLTC is also higher than Surge Reliable in the average number of hops at the beginning of data transmission, but with the MRLTC network topology gradually optimized, the average number of hops of MRLTC reduces gradually compared to Surge Reliable, and remains at a low value which has a high stability. Statistics show that the average number of hops of Surge Reliable in data transmission is 12.71494 while the number of MRLTC is 11.07987.

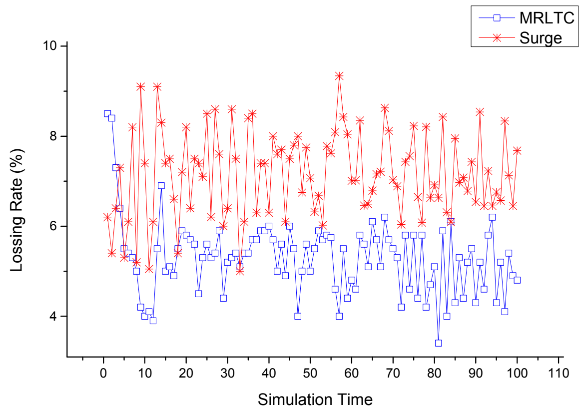

Fig. 3. Data transmission packet loss rate.

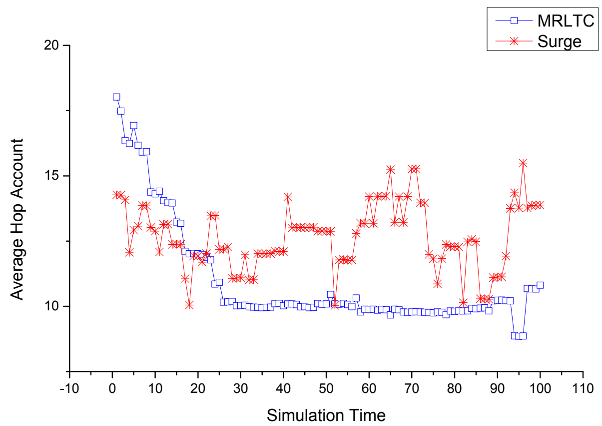

Fig. 4. Average number of hops of data transmission.

The performance of MRLTC is not perfect, but with the application running in-depth, its topology and data forwarding path optimize gradually and the corresponding data transmission quality is improved due to collaborative Multi-Agent Reinforcement Learning mechanisms.

Experiment 2: 50 nodes (including the sink node) randomly deployed in a 200 m × 200 m region (Fig.5), 100 nodes (including the sink node) randomly deployed in a 300 m × 300 m region (Fig. 6), 150 nodes (including the sink node) randomly deployed in a 300 m × 300 m region (Fig.7), 200 nodes (including the sink node) randomly deployed in a 500 m × 500 m region (Fig.8), they respectively investigate the average energy consumption of nodes for Surge Reliable and MRLTC in the data transmission stages.

The average distance between nodes is assumed as 20 m; The energy of sink node is abundant, the communication distance is 50 m; the total energy of general nodes is10 kJ, the communication distance is 30 m, When the residual energy is less than 0.1 % of the total energy, stop operating; taken in formula (7) c_{ij} is 0, the formula (9) α is 0.3, γ is 0.2, δ_1 is 0.5, δ_2, δ_3 are 0.25 (Table 2). Every 200 ms simulation time each node generates a data packet, in the wireless communication model set for different links with each type of packet loss rate.

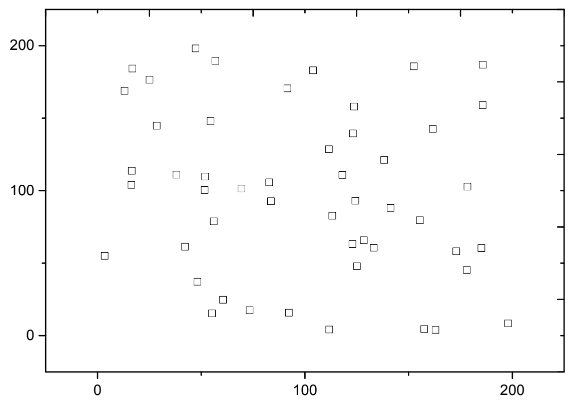

Fig. 5. Scene 1 with 50 nodes in Experiment 2.

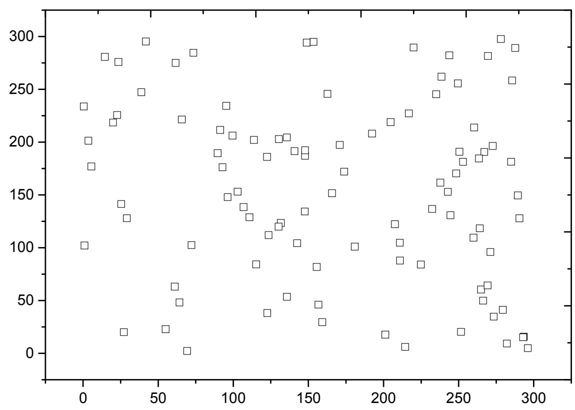

Fig. 6. Scene 2 with 100 nodes in Experiment 2.

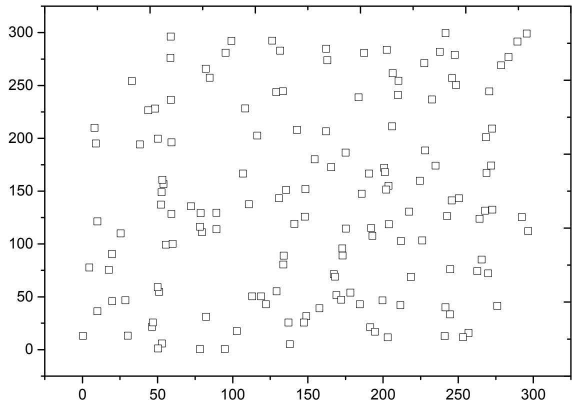

Fig. 7. Scene 3 with 150 nodes in Experiment 2.

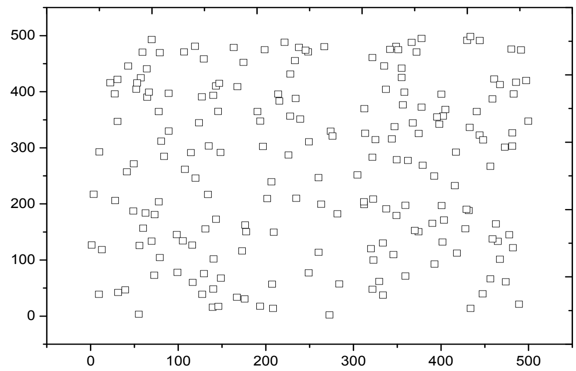

Fig. 8. Scene 4 with 200 nodes in Experiment 2.

Table 2. Simulation parameters.

Parameter type	Parameter value
c_{ij}	0
α	0.3
γ	0.2
δ_1	0.5
δ_2	0.25
δ_3	0.25

Repeat simulation 10 times with 400 s, calculating the average energy consumption of the node, shown in Fig. 9.

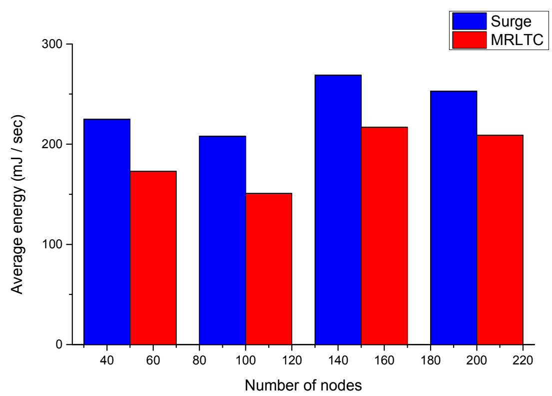

Fig. 9. Energy consumption of the node.

In the random deployment scenarios for different nodes, the average energy consumption of MRLTC node is less than Surge Reliable, compared to Surge Reliable, MRLTC improve energy efficiency. Thus, the collaborative Multi-Agent Reinforcement Learning mechanism has wireless sensor network topology and data forwarding path gradually optimized, reduce the average number of hops for data transmission, and save communication energy consumption.

6. Conclusion

The characteristics and application requirements of the wireless sensor network make the settlement to the topology control problem different from other traditional networks. In view of adaptive wireless sensor network topology control algorithm, which founded upon random deployment and based on collaborative multi-Agent reinforcement learning, this chapter consists of the following steps: Firstly, abstracting the wireless sensor network into cooperative problem-solving and multi-Agent systems, so the multi-Agent system model based on collaboration diagram can be received. Secondly, localizing multi-Agent Reinforcement Learning Collaboration global evaluation function of topology control by means of SparseQ, so the abstraction of topology control problem based on payment can be obtained. Lastly, topology control algorithm based on collaborative multi-Agent reinforcement learning is divided into two parts, initial topology formation and topology optimization. In the former stage, Initial topology and data forwarding path is generated by broadcasting and probing information of each Agent except for aggregation node, sending return information of aggregation node startup, exchanging return information from all Agents continuously. In the latter stage, the entire topology tends to optimize with constantly triggering return information through data forwarding, and with topology selection assessed value updated. The simulation analysis shows that, in random deployment mode, adaptive topology control algorithm has excellent overall performance when applied in the specific wireless sensor networks, such as data packet loss rate, average number of hops data transmission, average node energy consumption. etc.

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