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Clustering Routing Algorithm for Wireless Sensor Network Based on Mixed Strategy Game Theory

Baoying Wang,[1*] Yu Xia,[2] and Shuping Zhao[1]

[1]College of Electronics and Internet of Things, Chongqing College of Electronic Engineering, Chongqing 401331, China
[2]Chongqing Pump Industry Co., Ltd., Chongqing 400033, China

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We propose a clustering routing algorithm for wireless sensor networks (WSNs) based on mixed strategy game theory (CR-MSGT), which simulates the behavior of sensor nodes in a network through the mixed strategy model, so as to determine whether sensor nodes participate in the election of candidate cluster heads (CHs). The sensor nodes are randomly selected as CHs or common nodes according to their residual energy and the average energy of the network. Games are continuously played between nodes until the revenue function is maximized to reach the game equilibrium, thus proving the existence of the Nash equilibrium. Experimental results show that CR-MSGT can effectively extend the survivability of a network and mitigate the energy consumption of nodes.

1. Introduction

A wireless sensor network (WSN) has sensor nodes, which can perceive a certain range of environmental information, as the basic unit. In recent years, with the rapid adoption of the Internet of Things, the range of applications of WSNs has become increasingly extensive and now includes smart medical care,(1) smart transportation,(2) modern agriculture,(3) and warehouse management.(4,5)

For a WSN, the survival status of nodes affects the information perception ability of the entire network and determines the operating life of the network. Sensor nodes are usually driven by a limited amount of power, and their ability to calculate, store, and transmit data is also limited. Because of the large number of sensor nodes in most networks, battery replacement is generally unfeasible, so reducing node energy consumption and extending the network life are important research directions.

Cluster routing is an effective technology to solve the above problems, where the core idea is to divide the network into multiple clusters with each cluster having a node called the cluster head (CH). The task of communicating with the base station (BS) is completed by the CH node. The nodes in the network take turns acting as the CH. The CH integrates the information

*Corresponding author: e-mail: wangbaoying@cqcet.edu.cn
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collected by other nodes in the cluster, then forwards the information to the BS via a multi-hop or direct communication mode. The clustering mechanism can reduce the amount of forwarding data and shorten the data transmission distance of most nodes. However, the node acting as the CH consumes more energy than the other nodes in the cluster. Our task is to select the most suitable node in the network to act as the CH through game theory, which can balance the node load and energy.

Game theory provides a decision-making environment model that is interdependent and may exchange roles. In this paper, a clustering routing algorithm for a WSN based on mixed strategy game theory (CR-MSGT) is proposed.

2. Related Works

The low-energy adaptive clustering hierarchy (LEACH) algorithm and the distributed energy efficient clustering (DEEC) algorithm are two traditional sub-clustering routing algorithms.(6,7) In the LEACH algorithm, each node randomly generates a number between 0 and 1 to determine whether the node acts as the CH. Owing to the stochastic nature of this value, there may be an excessively large number of clusters during selection in each round and an uneven distribution of CHs in the network. The DEEC algorithm considers the residual energy of the node itself during the selection of the CHs, making the nodes with higher energy more likely to become CHs. However, because the distribution of CHs is disordered, some CHs may be distributed in the network edge zone, resulting in CH nodes consuming more energy for data transmission. Moreover, nodes at these positions are more likely to die, ultimately affecting the overall operation of the network. Game theory, through mathematical analysis, studies the course of action that is most beneficial to the decision-maker in the event of a conflict between players in a game.(8,9) It was first applied in the field of economics and later found to be applicable to WSN routing, and some game-theory-based cluster routing algorithms have been presented.

The game-theory-based distributed clustering approach (GTDCA) algorithm used to maximize the WSN lifetime establishes a CH game equilibrium model.(10) The nodes in the network are randomly declared as the CH with the equilibrium probability. The equilibrium probability is related to the income, cost, and the total number of network nodes when a node is declared to be the CH. However, the algorithm requires all nodes to participate at the same time, making the number of game participants large and the algorithm inefficient. The optimized clustering WSN algorithm based on game theory is a game-theory-based algorithm that partitions the network and employs a partition rotation mechanism to derive the region equilibrium probability according to the total number of nodes in each region.(11) Each region node randomly declares the CH with the equilibrium probability, but the algorithm requires sensor nodes to be evenly distributed in the network. Lin and Wang proposed a non-cooperative game model, in which sensor nodes declare whether they are CHs by computing the highest probability of maximizing revenue in a mixed strategy.(12) Li and Wu proposed a method combining a non-cooperative game with a distributed clustering algorithm to reduce the energy consumption of a network.(13) This method reduces the number of forwarding packets and extends the network life by collecting energy from the network.

3. System Model

3.1 Network model

The topology of the WSN in this study is shown in Fig. 1. The sensor nodes are randomly distributed in the monitoring area and can be divided into CH and common nodes, all of which have unique numbers. The nodes have the same function, do not have mobility, and can calculate the communication distance on the basis of the signal strength. To reduce the amount of data forwarding, the CH node adopts data fusion technology. The BS is usually located outside the monitoring area and is responsible for sending the information collected by the WSN to the end-user of the information. Its energy is not limited and it usually has an unlimited communication capability. A sensor node usually includes four functional modules: sensor, data processing, communication, and energy supply modules.(14) The sensor module is mainly responsible for the perception and collection of data and converts analog signals into digital signals. The data processing module is mainly responsible for data processing, such as data fusion. The communication module oversees information transmission between nodes. The energy supply module is responsible for the energy management of the node.

3.2 Energy consumption model

The traditional energy consumption model is used for the sensor node.(15) The free space model is used to calculate the energy consumed by a node in forwarding information when the distance that the node transmits information is less than the distance threshold.(16) Using a multipath fading model,(17) the node calculates the energy consumed by a node in forwarding information when the distance is greater than or equal to the distance threshold. Specifically, when the nodes send and receive one bit of data, the energy consumption is as follows:

$$E_{tx}(k)=\begin{cases} kE_{elec}+k\varepsilon_{fs}d^2, & d<d_0, \\ kE_{elec}+k\varepsilon_{mp}d^4, & d\geq d_0, \end{cases} \tag{1}$$

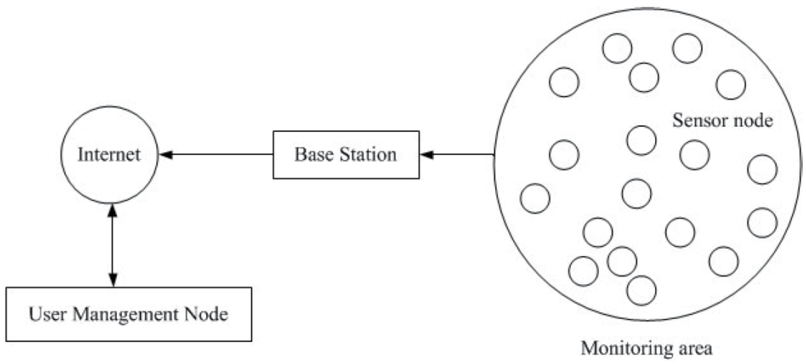

Fig. 1. WSN topology diagram.

$$E_{rx}(k) = kE_{elec}, \tag{2}$$

where E_{elec} is the energy consumption of sending or receiving one bit of data, E_{tx} is the energy consumption of transmitting k bits of data, E_{rx} is the energy consumption of transmitting k bits of data, ε_{fs} is the power amplification energy consumption coefficient under the free space model, ε_{mp} is the power amplification energy consumption coefficient under the multipath fading model, and d_0 is the critical distance for selecting the two transmission models, calculated as

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}. \tag{3}$$

4. Mixed Strategy Game Model

4.1 Definition of mixed strategy

In a game model, a pure strategy refers to the case that participants can choose only one strategy, whereas in a mixed strategy, participants can choose different strategies with given probabilities. A mixed strategy is the spatial probability distribution of a pure strategy, which is a special case of a mixed strategy.

In regions with a communication radius of R and N sensor nodes, the game is represented by $G(N, S, U)$. The actions of nodes are organized in rounds, and in each round, sensor nodes can select policies from the strategy set $S = \{Y_{ch}, N_{ch}\}$, where Y_{ch} represents participation in the candidate CH election and N_{ch} represents nonparticipation in the candidate CH election. $p_i = (p_{i1}, p_{i2})$ $(0 \le p_{ik} \le 1,\ p_{i1} + p_{i2} = 1)$ indicates that sensor node i participates in the candidate CH election with probability p_{i1} and does not participate with probability p_{i2}. The N sensor nodes participate or do not participate in the candidate CH election with probability $p = (p_1, p_2, \ldots, p_N)$ as the mixed strategy of this paper. U represents the network utility, which is formulated as a revenue cost model, and different selection strategies for sensor nodes yield different gains. To maximize the network utility, the sensor node selects strategy Y_{ch} as a candidate CH or strategy N_{ch} as a common node.

In the clustering algorithm, different nodes choose to become candidate CHs or common nodes with different probabilities, resulting in different revenue functions. To maximize the network utility, a mixed strategy game is formed between all sensor nodes.

4.2 Revenue function

In the cluster game model, when at least one sensor node j selects strategy Y_{ch} in the network, the revenue function of sensor node j is H and revenue functions of the other nodes are C. If no sensor node selects strategy Y_{ch}, then the gain of the revenue function is 0. C and H are given by

$$C = E(i) - C_{cm}, \tag{4}$$

$$H = E(i) - C_{ch}, \tag{5}$$

where $E(i)$ is the residual energy of the sensor node, C_{ch} is the cost of the sensor node becoming a CH, and C_{cm} is the cost of the sensor node becoming a common node.

The cost of the sensor node becoming a CH consists of three parts: the energy required to receive the packets from the cluster member, the energy required to integrate the data of the cluster members, and the energy required to transfer the packet to the BS, where Eqs. (1) and (2) are used for the energy calculation. The expression for C_{ch} is

$$C_{ch} = E_{rx(ch,i)} + E_{aggr} + E_{tx(ch,BS)}, \tag{6}$$

where E_{aggr} is the energy required to fuse the data of the cluster members.

The cost of becoming a sensor node is expressed as

$$C_{cm} = E_{tx(i,ch)}\,. \tag{7}$$

According to the above expressions, the revenue function expression $U(i)$ of node i is as follows.

$$U(i) = \begin{cases} H & \text{if } s_i = N_{ch} \text{ and } \exists j \in N, s_j = Y_{ch} \\ C & \text{if } s_i = Y_{ch} \\ 0 & \text{if } s_j = N_{ch}, \forall j \in N \end{cases} \tag{8}$$

Therefore, in the case of two sensor nodes involved in the CH game, the main function is shown in Table 1. Under the definition of a mixed strategy, the revenue function of each sensor node is also random because of the randomness of the strategy. In models having multiple sensor nodes with mixed strategies known to be $p = (p_1, p_2, \ldots, p_N)$, the revenue function of the network is

$$U = \sum_{i=1}^{N} p_i U(i). \tag{9}$$

Table 1
Revenue function of the cluster game of sensor nodes.

	Y_{ch}	N_{ch}
Y_{ch}	(C, C)	(H, C)
N_{ch}	(C, H)	0

4.3 Existence and solution of the Nash equilibrium

Theorem 1: In a game where sensor nodes select different strategies, strategy pairs (Y_{ch}, N_{ch}) and (N_{ch}, Y_{ch}) are a pair of Nash equilibrium strategies.

Proof: Strategies (Y_{ch}, Y_{ch}) and (N_{ch}, N_{ch}) have revenues (H, H) and 0, and strategies (Y_{ch}, N_{ch}) and (N_{ch}, Y_{ch}) have revenues (H, C) and (C, H), respectively. A sensor node with selection strategy Y_{ch} does not change the strategy selection to N_{ch}, so the gain is 0. Moreover, a sensor node that selects N_{ch} does not change the strategy selection to Y_{ch} because the gain becomes H. Thus, the strategy pairs (Y_{ch}, N_{ch}) and (N_{ch}, Y_{ch}) are a pair of Nash equilibrium strategies. In this model, multiple candidate sensor nodes play games in each region and select the node with the largest gain to become the CH.

Theorem 2: For a game where N sensor nodes participate, a multiplayer Nash equilibrium strategy will appear, namely, the selection strategy of one sensor mode is Y_{ch} and that of the remaining sensor nodes is N_{ch}.

Proof: In a mixed Nash equilibrium game, each participant has a probability distribution $p = (p_1, p_2)$ with the same gain, where p_1 is the probability of the node joining the candidate CH election and $p_2 = 1 - p_1$ is the probability of the node becoming a common node with the participant not joining the candidate CH election. Then, $U_{Y_{ch}} = H, U_{N_{ch}} = C \cdot [1-(1-p_1)^{N-1}]$.

By the definition of a mixed Nash equilibrium, the choice of each sensor node has the same utility, namely, $U_{Y_{ch}} = U_{N_{ch}}$. By calculation, we obtain

$$\begin{aligned} &U_{Y_{ch}} = U_{N_{ch}} \to H = C \cdot [1-(1-p_1)^{N-1}] \to \frac{H}{C} = [1-(1-p_1)^{N-1}], \\ &(1-p_1)^{N-1} = 1-\frac{H}{C} \to 1-p_1 = \left(1-\frac{H}{C}\right)^{\frac{1}{N-1}} \to p_1 = 1-\left(1-\frac{H}{C}\right)^{\frac{1}{N-1}}. \end{aligned} \tag{10}$$

Therefore, during a game with multiple sensor nodes, there is a Nash equilibrium that maximizes the gain.

For N sensor nodes, a mixed strategy combination is specified as $p^* = (p_1^*, p_2^*, \cdots, p_N^*)$. For each sensor node, the following conditions should be satisfied when the Nash equilibrium is reached:

$$U_i(p_i, p_{-i}^*) \le U_i(p_i^*, p_{-i}^*). \tag{11}$$

Then, p^* is called a mixed strategy Nash equilibrium, which is the optimal strategy combination. When p_i is a real number interval and the revenue function is differentiable, the Nash equilibrium can be solved using the extremal method. If p^* is a Nash equilibrium, then p^* satisfies

$$\frac{\partial U_i}{\partial p_i}\Big|_{p=p^*} = 0, \ i = 1, 2, \cdots, N. \tag{12}$$

The Nash equilibrium can be solved by solving the above N equations, yielding the optimal selection strategy for multiple sensor nodes under the mixed strategy.

5. Cluster Routing Algorithm Based on Mixed Strategy Game

In this paper, the algorithm refers to the LEACH protocol,[18] which is performed periodically and consists of three stages: network initialization, cluster establishment, and stable communication. In the cluster establishment stage, the main task is the selection and determination of candidate CHs, and cluster formation. The procedure of the algorithm is shown in Fig. 2.

5.1 Network initialization

In the implementation of this algorithm, the network should first be initialized. Assuming that all sensor nodes are randomly distributed in a region, each sensor node can adjust its own transmit power to adjust the communication radius. Upon receiving the broadcast message from the BS, all nodes record the distance from the BS and adjust the optimal transmission power to communicate with the BS. In the first deployment, all sensor nodes broadcast messages within the same communication radius R. The nodes receiving the message determine the neighbor nodes within the communication radius R and are stored in the list of neighbor nodes.

5.2 Establishment of cluster

5.2.1 Candidate CH election

After the network initialization, the sensor nodes can choose to be the CH or common node of the cluster, and their strategy can be changed in each round. To improve the quality of CHs, in the start key phase, the average energy in the network is calculated from the number of surviving nodes and the residual energy. The amount of residual energy and the average energy for each node are then compared, and only the nodes with residual energies greater than the average energy are included in the candidate CH node set. Each CH node in the set produces a random number between 0 and 1.

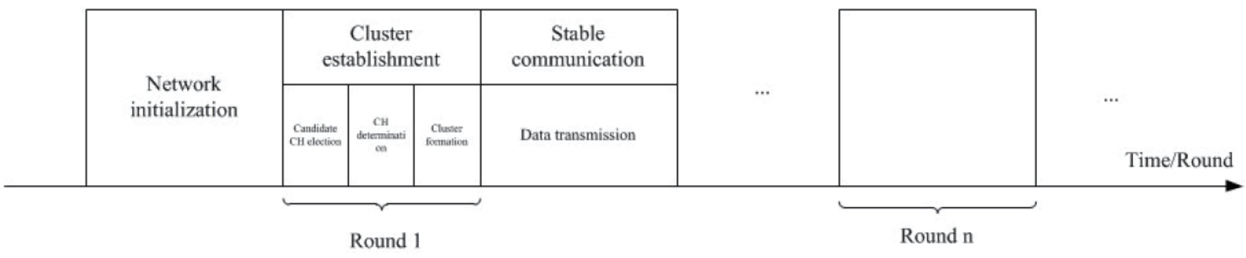

Fig. 2. Procedure of CR-MSGT.

5.2.2 Identification of CH

If there is only one sensor node selection strategy Y_{ch} in the candidate CH stage within a cluster group, the node automatically becomes the true CH. If there are two or more node selection strategies Y_{ch}, the present game model is used to reduce the energy consumption difference between CHs. At the same time, the game model balances the node energy consumption so that only one node within a cluster group is elected as the CH while maximizing the utility of all nodes in this game.

5.2.3 Cluster group formation

After all the CHs are determined, each CH adjusts the transmit power to send data to the BS and broadcasts the message within the communication radius. When the common sensor nodes receive the message, they select the nearest CH to join the cluster group.

5.3 Stable communication

After the completion of the clusters, the WSN enters the stable data communication stage, in which the main task is to send the collected data to the BS through the CH of each cluster. By scheduling the CH, the members of the cluster send data to the CH in a coordinated manner by time-division multiplexing. After receiving data from all nodes in the cluster, the CH preprocesses and fuses the data and sends it to the BS.

6. Results and Discussion

6.1 Parameter settings

In this study, MATLAB is used for simulations to verify the performance of CR-MSGT in comparison with those of LEACH,(6) a classical classification algorithm, and GTDCA,(10) a game-theory-based classification routing algorithm. In our simulations, 100 sensor nodes are randomly deployed in a 100 × 100 region, the initial position of the BS is (150, 50), and the specific parameters are shown in Table 2.

6.2 Algorithmic performance analysis

Figure 3 shows the number of surviving nodes after different numbers of network cycles for each algorithm. For the same number of network cycles, the number of surviving nodes increases in the order LEACH < GTDCA < CR-MSGT. When the last node dies, the number of network cycles of CR-MSGT is significantly larger than those of LEACH and GTDCA. The CH selection of CR-MSGT considers the average energy of the remaining nodes to balance the overall energy consumption of the network and avoid the premature death of nodes, making the choice of the CH more reasonable.

Table 2
Parameter settings.

Parameters	Value
Network area	100 × 100
Number of nodes	100
BS location	(150, 50)
Package size	2000 bit
Control package size	200 bit
E_{elec}	50 nJ/bit
ε_{amp}	0.0013 pJ(bit/m^4)
ε_{fs}	10 pJ(bit/m^2)
E_{aggr}	5 nJ/(bit/message)
Initial energy of node	1 J

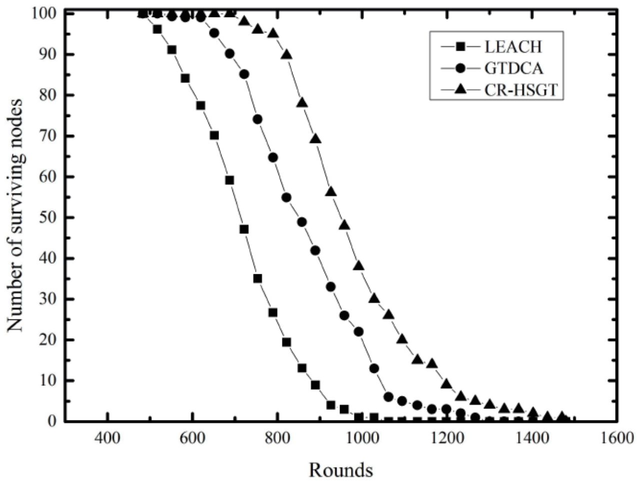

Fig. 3. Number of surviving nodes after different numbers of network cycles.

Figure 4 shows the change in network residual energy with increasing number of network cycles. According to the figure, when the network works stably, CR-MSGT shows a greater network residual energy than the other two algorithms for the same number of network cycles. The other two algorithms have too many or too few clusters, which are evenly distributed, resulting in too fast network energy consumption.

Figure 5 shows a comparison of network lifetimes obtained when the first node dies, half the nodes die, and the last node dies in the network. CR-MSGT extends the times of the deaths of the first and last nodes in the network. Compared with the cases of LEACH and GTDCA, the death of the first node in CR-MSGT is delayed by 196 and 148 rounds, and the time when half the nodes die is delayed by 222 and 90 rounds, respectively.

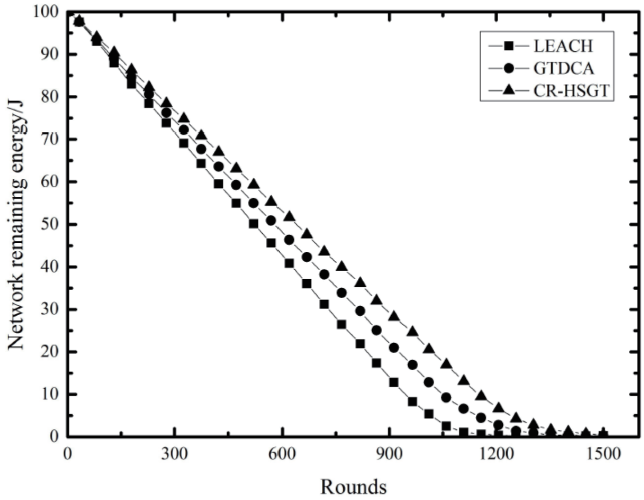

Fig. 4. Network residual energy after different numbers of network cycles.

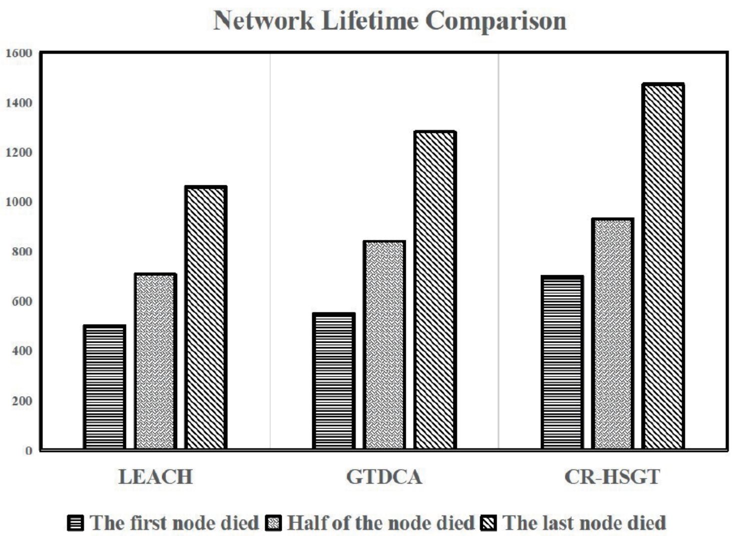

Fig. 5. Comparison of network lifetimes.

7. Conclusions

Toward solving the clustering routing problem in WSNs, we propose an algorithm based on CR-MSGT in this paper. All sensor nodes choose whether to become the CH with a random probability, resulting in a mixed strategy game model. In accordance with the mixed strategy game model, the CH node set in the network is determined in order to form clusters and carry out stable communication. Experimental results show that the proposed algorithm can effectively balance the energy consumption of nodes, thereby prolonging the life of the network.

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About the Authors

Baoying Wang received her B.S. degree in industrial automation from Northeast Petroleum University (NEPU), China, and her M.S. degree in Microelectronics and Solid-State Electronics from Chongqing University of Posts and Telecommunications (CQUPT), China, in 2001 and 2009, respectively. She joined College of Electronics and Internet of Things, Chongqing College of Electronic Engineering in 2009, and underwent communication and professional training in University of Amiens, France, from September to November 2018. In recent years, she has published three academic monographs, six invention patents, and nearly 20 academic papers, and presided over and participated in four provincial projects. Her interests include automation and IoT. (wangbaoying@cqcet.edu.cn)

Yu Xia received his B.S. degree in industrial automation from Northeast Petroleum University (NEPU), China, in 2001. He currently works for Chongqing Pump Industry Co., Ltd. and is a member of National Enterprise Technical Center. His interests include industrial automation and IoT. (30539562@qq.com)

Shuping Zhao received her M.S. degree in optical engineering from University of Electronic Science and Technology of China (UESTC), China, in 2006. She currently works for College of Electronics and Internet of Things, Chongqing College of Electronic Engineering. In recent years, she has published three academic papers. Her interests include automation and IoT. (9387796@qq.com)