Resource Allocation Based on Chaotic Ant Colony Algorithm in Self-organizing Wireless Sensor Network

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Abstract. A resource allocation scheme based on chaotic ant colony algorithm in self-organizing wireless sensor network is proposed, and corresponding chaotic sequence generator is designed in this paper. Simulations are conducted to compare the proposed method with conventional genetic algorithm and dynamic programming algorithm under self-organizing wireless sensor network environment. Results show that compared with the scheme based on dynamic allocation algorithm and conventional genetic algorithm, the scheme based on chaotic ant colony algorithm has higher target detection rate and lower power consumption, which also extends the networks lifetime.

1. Introduction

With the development of wireless sensor network, more and more people pay attention to the wireless sensor network with self-organizing properties. Self-organizing wireless sensor network is formed with large number of sensor nodes, which randomly deploy in the monitoring environment with wireless communication capabilities. [1] With the sensor nodes sending and receiving a variety of observed information spontaneously, the self-organizing wireless sensor network takes a wide range of applications in industry control, disaster warning and battlefield surveillance with advantages of rapid deployment and strong resistance to destruction. [2] However, each sensor has very limited battery energy, which is also difficult to replace battery. [3] Furthermore, the single sensor communication range is limited and non-centralized control. [4] Traditional resource allocation cannot meet new features of self-organizing wireless sensor network. Therefore more flexible and intelligent resource allocation scheme needs to be designed to allocate targets and node residual energy.

In order to save node battery energy and improve target detection rate, many scholars have studied the resource allocation for self-organizing wireless sensor network deeply. Resource allocation scheme based on dynamic programming algorithm is presented in literature [5]. It uniformly configures and schedules targets in the way of centralized control, which improves the network efficiency. But the scheme controls all sensor nodes in the entire network simultaneously, which is difficult to achieve in self-organizing wireless sensor network. Literature [6] proposes a resource allocation scheme based on conventional genetic algorithm. It improves target detection rate and resource utilization through iterative calculation, which also extends lifetime of the sensor nodes. However, in this scheme the conventional genetic algorithm is easy to fall into premature convergence. When the number of the nodes is large, it may fall into evolutionary stagnation and converge to the sub-optimal solution. A scheme based on T-MAC protocol is proposed in literature [7], which adaptively adjusts the listening time slot of the sensor nodes. The scheme improves the energy efficiency of the self-organizing wireless sensor network. But with this scheme the sensor nodes sleep early and have high communication delay. Literature [8] proposes a scheme based on Z-MAC protocol with high channel
utilization and low latency. In low throughput condition, it adaptively adjusts the access time slot in self-organizing wireless sensor network with high efficiency. But in high throughput condition, the complexity of the scheme is too high, which is hard to get the results in real-time conditions [9-10].

This paper presents a resource allocation scheme based on chaotic ant colony algorithm (CACA) in self-organizing wireless sensor network. With the features of limited energy, limited computing power and distributed control, the CACA scheme allocates the resource of sensor nodes and monitoring targets with heuristic chaotic ant colony algorithm. Chaotic ant colony algorithm initializes and adaptively adjusts the parameters using chaotic sequence, and then adaptively changes the parameters of self-organizing wireless sensor networks. For rationally allocating network resource and node residual energy, chaotic ant colony algorithm adaptively allocates the targets to active sensors.

Simulations are conducted for resource allocation by using CACA, scheme based on genetic algorithm (GA) and scheme based on dynamic programming algorithm (DPA), respectively. Results show that, the performance of CACA scheme is significantly better than GA and DPA in self-organizing wireless sensor network. It has higher target detection rate and lower power consumption, which also extends the networks lifetime.

2. System Model

2.1. System Model of Self-organizing Wireless Sensor Network

Self-organizing wireless sensor network consists of gateway nodes, cluster head nodes and sensor nodes. The sensor nodes and cluster head nodes are divided into several different clusters, and each cluster has a cluster head node. Information perceived by sensor nodes is transmitted to cluster head nodes firstly, and then to gateway nodes through single hop or multi-hop communication.

Self-organizing wireless sensor network is a hierarchical structure. From top to bottom, it can be divided into application layer, transport layer, network layer, data link layer, and physical layer. Self-organizing wireless sensor network have some features, such as low power consumption, distributed control and self-organizing, etc. As the communication capacity is limited, a node which has strong communication capacity and storage capacity within the region is usually chosen to be the cluster head node, and other sensor nodes communicate and exchange data with it directly or indirectly, which forms a multi-hop self-organizing network through the wireless communication.

Wireless sensors in self-organizing wireless sensor network have some characteristics, such as limited range of perception, small communication radius, self-organizing cluster and limited battery energy, etc. These features increase the complexity of resource management, as the network must select the nodes which have more residual energy and coverage range to work. In this way, the network can extend the lifetime and ensure the cluster cover the entire monitoring area, avoiding monitoring blank area.

2.2. Design of Chaotic Sequence Generator

In order to ensure a simple structure, traditional chaotic sequence generator often uses one-dimension logistic map. 1-D logistic map is sensitive to initial values, and has characters of non-convergence, difficult to predict long-term behavior, etc. However, with the size of problem increasing, 1-D chaotic map’s blank window and uneven distribution easily lead to poor efficiency.

In order to ensure random uniform of the generated chaotic sequence, we generate chaotic sequences by using 2-D Kopel map, which is shown as follows:

$$\begin{align*}
x_{n+1} &= (1 - \rho)x_n + \rho \mu y_n (1 - y_n) \\
y_{n+1} &= (1 - \rho)y_n + \rho \mu x_n (1 - x_n)
\end{align*}$$

(1)

Where, $\rho$ and $\mu$ are constant factors, and $x_n$ and $y_n$ are discrete chaotic variables. When $\rho = 1.2$, $\mu > 3.0078$, the system is in a completely chaotic state. If $x_{n+1} = x_n$, $y_{n+1} = y_n$, the four fixed initial points at are $P_1(0,0)$, $P_2(0.6675,0.6675)$, $P_3(0.6368,0.6956)$ and $P_4(0.6956,0.6368)$, respectively. Jacobian matrix determinant of two-dimensional Kopel chaotic systems is shown as (2):
Chaotic sequence generated by 2-D Kopel map can effectively ensure the uniform random, ergodic property and sensitivity for initial values, which can also avoid blank window, uneven distribution, etc. Using 2-D Kopel chaotic sequence in ant colony algorithm can effectively improve the searching accuracy and efficiency, and promote pheromone positive feedback. After joining the chaotic disturbance, ant colony algorithm can find the optimal solution more quickly and accurately, which reduces the time complexity of the algorithm and effectively avoids falling into local optimum solution.

3. Resource Allocation in Self-organizing Wireless Sensor Network Based on Chaotic Ant Colony Algorithm

Ant colony algorithm is an intelligent algorithm, which can global search the entire solution space and effectively avoid local sub-optimal solution. However, traditional ant colony algorithm searches the entire solution space without taking full advantage of feedback information, which causes redundant iterations and inefficiency. To overcome these shortcomings, this paper presents a resource allocation scheme in self-organizing wireless sensor network based on chaotic ant colony algorithm, which adaptively adjusts parameters using feedback information accumulated in the course of algorithm running. This resource allocation scheme also uses chaotic sequences to initialize pheromone and takes chaotic disturbance. It speeds up the convergence rate and efficiency, and avoids unnecessary redundancy iterations. The main steps of chaotic ant colony algorithm are: building ant colony system model, initializing intensity of pheromone trails, setting transition probability, updating and chaotic disturbing pheromone evaporation rate, adaptively adjusting parameters of the algorithm, and so on.

3.1. Building Ant System Model

In large-scale self-organizing wireless sensor network, the CACA scheme establishes ant system model according to the number of targets within each cluster, node residual energy, node sensing radius, and target priority, etc. Each ant path represents a kind of resource allocation, and all the possible paths constitute the whole solution space. Assuming that there are $M$ sensor nodes, $L$ targets, and each sensor node can monitor $N$ targets, then the resource allocation model can be shown in Figure 1.

![Figure 1. Ant system model in self-organizing wireless sensor network system](image-url)
In Figure 1, each row represents a target to be detected, and each column represents a sensor node. The number in rectangle represents the target number to be monitored by the sensor. In the process of running, ants start from the No. 1 sensor. After $M$ steps, it arrives at No. $M$ sensor. As the traversal process repeated $N$ times, each sensor gets $N$ different monitoring targets, which creates a new resource allocation scheme.

3.2. Initializing Intensity of Pheromone Trails
There is an equal value of pheromone on each path in traditional ant colony algorithm at the initial time, which leads to the ants selecting path with equal probability in initial stage. As lack of heuristic information, the ant is difficult to find a preferable path in a short time, resulting in slow convergence.

Chaotic ant colony algorithm initializes the intensity of pheromone trails with Kopel chaotic sequence. First, we get a certain number of random sequences which is generated by Kopel chaotic sequence generator, $\{x_1, x_2, \cdots, x_M\}$, $\{y_1, y_2, \cdots, y_M\}$, as shown as (1). Each random sequence corresponds to an initial path. Then, select a certain percentage of preferable paths, and give these paths more quantity of pheromone, so that the ants can find the suitable one to speed up the pace of algorithm convergence.

3.3. Setting Transition Probability
While solving the problem of resource allocation with chaotic ant colony algorithm, the probability of moving from $i$ to $j$ at $l$-step is shown as follows:

$$P_{ij}^l(t) = \frac{\tau_{ij}^a(t)\eta_{ij}^p(t)}{\sum_{j=1}^{M} \tau_{ij}^a(t)\eta_{ij}^p(t)}, \quad i, j \in \{1, 2, 3, \cdots, L\} \quad k \in \{1, 2, 3, 4, M\}$$

(3)

In equation (3), $P_{ij}^l(t)$ is the probability of ants moving from $i$ to $j$ at $l$-step, $t$ is the number of algorithm iterations, and $\tau_{ij}^a(t)$ is pheromone at $k$-step, which is the pheromone accumulated in the process of moving by the former ants. $\eta_{ij}^p(t)$ is the visibility factor, reflecting the heuristic information in the path selection. The two parameters $\alpha$ and $\beta$ are used for index correction for $\tau$ and $\eta$, reflecting value of pheromone accumulated in the process of moving by ants and relative weight of heuristic information in the routing respectively. Ants start from the first sensor node, and continue to choose step according to $P_{ij}^l(t)$ until reaching the last one. After $N$ times traversing, the ants chose $N$ kinds of resource allocation routes and aggregate to produce a new resource allocation scheme.

3.4. Updating and Chaotic Disturbing Pheromone Evaporation Rate
After $m$ steps forward, the ants complete a cycle path. When all the ants in the colony complete the traversing, they release appropriate number pheromone. The quantity of pheromone on the path can be shown in equation (4):

$$\tau(t+1) = \rho \times \tau(t) + \Delta \tau(t, t+1) + q C_{ij}$$

(4)

In (4), $\tau(t)$ and $\tau(t+1)$ are quantity of pheromone on the path in $t$ iteration and $t+1$ iteration respectively. Volatile factor $\rho$ is a positive number less than 1, which represent the pheromone evaporation rate after a cycle, and $(1-\rho)$ is attenuation coefficient of pheromone value. $C_{ij}$ is the chaotic sequence generated by 2-D Kopel map. $q$ is a constant factor. $\Delta \tau(t, t+1)$ is the value of pheromone released by the ants between $t$ iteration and $t+1$ iteration, which is as follows:

$$\Delta \tau(t, t+1) = \sum_{p=1}^{M} \Delta \tau^{(p)}(t, t+1)$$

(5)
In (5), $P$ is the number of ants in the colony. $\Delta r^{(p)}(t,t + 1)$ is the value of pheromone released by the number $p$ ant between $t$ iteration and $t + 1$ iteration. The quantity of pheromone released by ant at $l$-step can be shown as formula (6):

$$
\Delta r^{l}_{ij}(t,t + 1) = \begin{cases} 
kQ_p & \text{if the } n_{ij} \text{ ant passed route } (i, j) \\0 & \text{otherwise}
\end{cases} \tag{6}
$$

In (6), $k$ is constant factor, representing the quantity of pheromone released by ant per unit length. $Q_p$ is the length of path traveled by number $P$ ant, which takes $M$ steps forward for a cycle. It represents the number of targets perceived by self-organizing wireless sensor. After the release of pheromone, the path which can detect more targets has a large concentration of pheromone. So the probability of the path chosen by ants next time is larger, thus form a positive feedback process. It is eventually able to get an optimal solution by iteration.

3.5. The Basic Flow of Chaotic Ant Colony Algorithm

The basic flow of resources allocation by chaotic ant colony algorithm is shown as follows. First, establish an ant colony system model according to the number of sensors, and set the maximum number of targets that each sensor can detect. Then initialize pheromone trajectory using Kopel chaotic sequence, and move the ants according to the transition probability. After evaluating the ant fitness, update the pheromone, and adaptively adjust the transition probability to continuously improve the result of the resources allocation scheme with ant colony algorithm. Finally, if reach the specified generation, output the optimal resource allocation scheme, or continue to run the algorithm until reaching the specified number of iterations.

4. Simulation and Results

In the simulation, the interference between nodes at the edge of different cluster is ignored. The monitoring area is $450 \times 450 \text{m}^2$. The nodes’ effective sensing radius is 40m, and cluster radius is 120m. The number of ants in chaotic ant colony algorithm is 40, and the maximum number of iterations is 50. We set $\alpha = 2.5$, and initialize evaporation coefficient $\rho = 0.65$. Assuming that each sensor can monitor five targets, and each target needs to be monitored by three sensors simultaneously.

Figure 2 shows the comparison of lifetime/round with the number of dead nodes, with the scheme based on chaotic ant colony algorithm, genetic algorithm and dynamic programming algorithm under the conditions of different targets number. The network lifetime is defined as the time of the first node using up energy. It can be seen from Figure 2 that the lifetime of genetic algorithm and dynamic programming algorithm is shorter than chaotic ant colony algorithm with the same initial energy, because the genetic algorithm and dynamic programming algorithm do not dynamically change the algorithm parameters in the process of running. Although some nodes survival time in genetic algorithm and dynamic programming algorithm is relatively long, most of nodes’ energy in the network has run out. As the integrity of the network has been damaged, it cannot work normally. Chaotic ant colony algorithm selects the node which has more residual energy priority for perception and communication, which ensure the energy consumption evenly distributed throughout the whole network and nodes death time more uniform. Chaotic ant colony algorithm not only ensures the integrity of the network during working time, but also improves the networks lifetime compared with the other two algorithms.
Figure 2. Network lifetime/round with the number of dead nodes
(a) 200 targets  (b) 300 targets  (c) 400 targets  (d) 500 targets

Figure 3 shows the comparisons of targets number successfully detected by sensors in three algorithms under the conditions of different targets number. It can be seen from the simulation results that, the dynamic programming algorithm detects fewer targets, and its performance is unstable with the number of sensors growing. When there are few sensors, the performance of genetic algorithm is good. It detects more targets than dynamic programming algorithm does. But with the increasing of sensors’ number, GA began to premature convergence, leading to the target number detected increasing slowly. Chaotic ant colony algorithm initialize intensity of pheromone trails with chaotic sequence in the initial stage of iterations, and dynamically adjusts the value of pheromone through chaotic disturbance. So it can avoid premature convergence and can successfully detect more targets.

Figure 3. Number of detected targets with sensors’ number
(a) 200 targets  (b) 300 targets  (c) 400 targets  (d) 500 targets
5. Conclusions
With the rapid development of self-organizing wireless sensor network, there is an urgent need for resource allocation scheme which has high efficiency, good real-time performance and low energy consumption. Therefore, a resource allocation scheme based on chaotic ant colony algorithm is presented in this paper. Simulation results show that, the CACA scheme effectively increases the number of detected targets. It not only reduces system energy consumption, but also extends the self-organizing wireless sensor network lifetime, which improves the network overall performance.

6. Acknowledgements
The authors declare that there is no conflict of interest regarding the publication of this paper. This paper is supported by the National Nature Science Foundation of China (No. 61962053) and High-level talent research project of Shihezi University (No. RCZK2018C39).

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