Cluster Heads Election Analysis for Multi-hop Wireless Sensor Networks Based on Weighted Graph and Particle Swarm Optimization*

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Abstract

Continued advances of wireless communication technologies have enabled the deployment of large scale wireless sensor networks. The sensors' limited power makes energy consumption a critical issue. In single-hop wireless sensor networks, cluster heads election method based on residual energy can obtain better energy efficiency than the method in which cluster heads are elected in turns or by probabilities. Is it the same in multi-hop wireless sensor networks? In this paper we proposed and evaluated a routing optimization scheme based on graph theory and particle swarm optimization algorithm for multi-hop wireless sensor network. Our algorithm synthesized the intuitionist advantages of graph theory and optimal search capability of PSO. The result in multi-hop networks is completely different from that in single-hop wireless sensor networks. The result shows that there is very little difference from these methods. The reason is discussed in detail.

1. Introduction

Continued advances of wireless communication technologies have enabled the deployment of large scale wireless sensor networks (WSNs) [1]. Sensor nodes monitor the surroundings and process the data obtained and transmit this data to the base station located on the periphery of the sensor network. Each sensor node is equipped with a limited battery-supplied energy which makes energy consumption a critical issue. Innovative techniques are highly required to improve energy efficiency and prolong the lifetime of WSNs.

Many energy-efficient solutions have been put out. An approach that is likely to succeed is the use of a hierarchical structure [2]. Clustering is an important technique in this respect which aims at generating the minimum number of clusters and transmission distance. The clustering algorithms also distinguish themselves by how the cluster heads are elected. Banerjee et al. presented an efficient distributed clustering algorithm to create a hierarchical control structure and the set of desired clusters [3]. WSN is viewed as an unweighted connected graph and a cluster is defined as a subset of vertices.

Clustering problem can be viewed as a search problem through a typically NP-hard solution space. In this sense, some researchers have adopted nature-inspired approaches for WSNs. Tillett et al. proposed a particle swarm optimization (PSO) algorithm to cluster sensors in a sensor network [4]. Guru et al. also proposed the particle swarm optimizers to cluster information in WSNs [5]. They formulate the clustering method as a minimization problem. The PSO approach to determine optimal divisions is shown to be more robust.

In this paper, we proposed and evaluated a routing optimization scheme based on graph theory and PSO for multi-hop WSNs. This method synthesized the intuitionist advantages of Banerjee's graph theory [3] and Tillett's PSO [4]. Most existing algorithms cannot be directly applied to multi-hop WSNs in which the transmission range of each node may be different. In single-hop WSNs, cluster heads election method based on residual energy can obtain better energy efficiency than the method in which cluster heads are elected in turns or by probabilities. But comparing results for multi-hop WSNs show that there is very little difference from these methods. The reason is discussed in detail.

2. Algorithm

2.1. Network Model

To specify the network model, we make the following assumptions about WSNs.

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All sensors and base station are stationary after deployment and the location of base station is known a prior. Each sensor has a unique pre-configured id. Initial energies of all sensors are known a prior. The communication is based on the multi-hop. The communication is symmetric and a sensor can compute the approximate distance based on the received signal strength if transmission power is given. The network has been clustered into different clusters by other clustering algorithm. We only consider the cluster head rotation mechanism in one cluster. All sensor nodes in the same cluster do not have any transmission range restriction.

We use a directional, weighted and connected graph *G(V,E)* for one cluster of a WSN. *V(G) = {V1, V2, …, Vn }* denotes the sensor nodes and *E(G)* denotes the edge between two nodes. A node *i* has a counter to calculate the residual energy E_i and the Euclid distance *d(i, j)* to each of the other node *j* after each transmission.

The algorithm proceeds to find all the spanning trees of the weighted graph. Then the optimal tree can be searched from all the spanning trees with the distance *d(i, j)* as the weight between node *i* and *j* in order to minimum the distance. This process can proceed by Kruscal algorithm which is proved to be a good algorithm in graph theory. There may be more than one optimal tree in the cluster. The optimal trees are selected based on the minimum distance only. The best routing can be searched from all the optimal trees by comparing energy consumption. Fig.1 shows the optimal tree of a network model with 20 nodes.

2.2. Cluster Heads Election Constraints

We assume the communication between sensor nodes and cluster heads is based on the multi-hop. Generally the researchers use single-hop communication between the sensor nodes and the cluster heads. They note that for the system parameters they investigate, multi-hop mode results in more energy expenditure than that in single-hop mode because the energy spent in transmitter/receiver electronics is comparable to the energy spent in the power amplifier. However, when we consider a general sensor network that may be deployed over a large region, the energy spent in the power amplifier related to distance may dominate to such an extent that using multi-hop mode may be more energy-efficient than single-hop mode.

In single-hop WSNs, cluster heads election method based on residual energy can obtain better energy efficiency than the method in which cluster heads are elected in turns or by probabilities. While is it the same in multi-hop WSNs? This is the question to be discussed.

Method 1(Energy method) [6]: The cluster heads are elected based on the residual energy E_i of the node and the Euclid distance *d(i, j)* to its neighbor node in the opti-

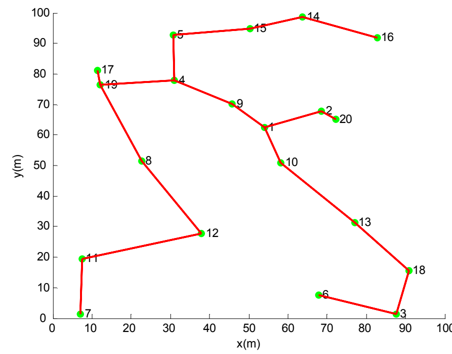


Figure 1. Optimal tree of the network model with 20 nodes

-mal tree. The distance *d(i, j)* is defined as:

$$d(i,j)=\sqrt{(x_j-x_i)^2+(y_j-y_i)^2} \quad (1)$$

Where (x_i, y_i) and (x_j, y_j) are the coordinates of node *i* and *j* separately. The initial energy for a node *i* is denoted by E_{0i}. At the beginning of a transmission, the residual energy E_i of a node *i* is equal to E_{0i}. Assuming that each node will be the cluster head. The energy dissipation for transmitting *b* bits data to the base station is

$$E_{direct-chi}=bE_{elec}(n-1)+bE_{DA}+bE_{elec}+b\varepsilon_{amp}d_{1i}^{2.5} \quad (2)$$

Where, E_{elec} is the energy consumption for transmitter or receiver startup. E_{DA} is the energy consumption in data fusion. ε_{amp} is the energy consumption coefficient of amplifier in data transmission. d_{1i} is the distance from node *i* to the base station. And *n* is the number of all the nodes in the cluster. We make the following formula about E_i, $E_{direct-chi}$ and the weight ω after repetitious experiments

$$\omega(i)=\frac{\eta E_i}{(1-\eta)E_{direct-chi}} \quad (3)$$

Where, η is a variable number between 0 and 1 which represents the proportion of the residual energy in cluster heads election. So $(1-\eta)$ represents the proportion of the transmission distance in cluster heads election. The node with the maximum weight will be elected as the cluster head. The non cluster head only transmit data to its neighbor node in the routing.

In the first round, energy consumption E_{chi} of the cluster head will be defined as:

$$E_{chi}=b(E_{elec}+E_{DA}+\varepsilon_{amp}d_{1i}^{2.5}) \quad (4)$$

For a non cluster head node *i*, the energy consumption $E_{non-chi}$ will be

$$E_{non-chi}=b(E_{elec}+\varepsilon_{amp}d_{2i}^{2}) \quad (5)$$

Where, d_{2i} is the distance from each non cluster node to its neighbor node in the routing. The residual energy of cluster node *i* after a round of transmission will be the difference between E_{0i} and E_{chi}. And the residual energy of non cluster node i will be the difference between E_{0i} and $E_{non\text{-}chi}$.

At the beginning of the second round, the weight ω is calculated by formula (3) repeatedly and the cluster head is elected again. The same process proceeds iteratively until the first node in the cluster runs out of energy.

In method 2 (Turns method) [6] and method 3 (Probability method) [7], cluster heads are elected in turns and by probabilities separately. The other steps are the same as that in method 1 (Energy method).

2.3. Routing Optimization Using PSO

PSO is an evolutionary computing technique based on principle such as bird flocking. This method was first proposed by Kennedy and Eberhart [8]. The solution to an optimization problem is developed using a number of particles each of which obtains its own solution. Each particle will have a fitness value, which will be evaluated by the fitness function to be optimized in each generation. Each particle knows its own best position *pbest* and the best position *gbest* among the entire group of particles. The particle will have velocities which direct the flying of the particle. In each generation the velocity and the position of the particle will be updated. The process for the optimization is

(1) Let $f(x)$ be a N-dimensional objective function to be optimized.

(2) Let there be several particles in the PSO scheme. Each of which generates a N-dimensional solution vector. If $x_i(n)$ is the solution of the i-th particle at the n-th iteration, the fitness value of the particle will be $f(xi(n))$.

(3) At the $(k+1)$-th iteration, each particle's solution $x(k)$ is updated by

$$\begin{aligned} v_i^{k+1} &= \omega' v_i^k + c_1(pbest_i - x_i^k) + c_2(gbest_i - x_i^k) \\ x_i^{k+1} &= x_i^k + v_i^{k+1} \end{aligned} \tag{6}$$

Where v_i^k is its velocity, $pbest_i$ is the particle's own best recorded position of $f(x)$ and $gbest_i$ is the best recorded position among particles in its neighborhood. Thus each particle belongs to a suitably defined neighborhood. The parameters c_1 and c_2 are probability variables that are uniformly distributed. The parameter ω' is the inner weight.

(4) Convergence is achieved when the best solution does not change substantially from iteration to iteration.

We now treat the routing finding and cluster head rotation problem as the objective optimization problem with each node behaving as a particle. The shortest distance and maximum energy in Energy method and node number in Turns method and random number in Probability method should be decided. In Energy method, we find that the fitness function involves two major topological properties, transmission distance and residual energy after a round of transmission. Our approach involves a heuristic search through the space of possible topologies that optimize these quantities. We find the fitness function has the same properties as the weight we mentioned in formula (3) and each node has a different fitness function. So we make the fitness function of the i-th node the same as the weight ω in the n-th generation.

In each iteration, the particle with the maximum fitness value will be elected as the cluster head. The iteration stops until the first node in the cluster runs out of energy or the total energy of the network reaches the assumed condition.

3. Results

We assumed that there are 20 sensor nodes in one cluster distributed randomly in a square M×M region. The parameters of the network are shown in Table 1.

Network lifetime is the performance metric being investigated. It represents the periods or rounds from the instant the network is deployed to the moment when the first sensor node runs out of energy. But the nodes in a cluster are distributed in the limited region and they may have similar information. The decrease of single or few nodes would not affect the QoS (quality of service) of the network. So we consider the rounds from the instant the network is deployed to the moment of half of the nodes still alive as the network lifetime. We compare the network lifetime in the three methods mentioned above when location of base station and distribution region are being changed. In order to ensure the accuracy of the simulation, we select the average in 50 times simulations.

4. Discussions

In single-hop WSNs, cluster heads election method based on residual energy can obtain better energy efficiency than the method in which cluster heads are elected in turns or by probabilities. But it is not the same in multi-hop WSNs as that in single-hop WSNs.

Fig. 2 shows the network lifetime comparison of the three methods in the smaller distribution region. This can be summarized in Table 2 and Table 3. We can see that the network lifetime of energy method is smaller than that of the other methods no matter whether the base station is located near the network or far from the network. The lifetime of the Probability method is the longest. And for the same method, the lifetime also has nothing to do with the location of base station.

In Fig. 3 for the larger distribution region, the same results can be seen again. The network lifetime almost has nothing to do with the base station location. This can be summarized in Table 4 and Table 5. The network lifetime by the energy method is still the smallest and the network lifetime by the Probability method is still the longest.

Table 1. Parameters of simulations

Location of Base Station	(0,0), (10,20) (100,0), (100,100)	(0,0), (50,100) (0,500), (500,500)
Area(M*M) (m^2)	20*20	100*100
Initial Energy	0.5J	
E_{elec}	50nJ/bit	
ε_{amp}	10pJ/bit/m^2	
E_{DA}	5nJ/bit/signal	
Packet Size	1000 bits	

Table 2. Network lifetime in rounds when first of the nodes died for a smaller region (20×20) m^2

Method	Base Station Location			
	(0,0)	(10,20)	(100,0)	(100,100)
Energy Method	272	364	399	394
Turns Method	406	406	406	405
Probability Method	403	403	403	398

Table 3. Network lifetime in Rrounds when half of the nodes died for a smaller region (20×20) m^2

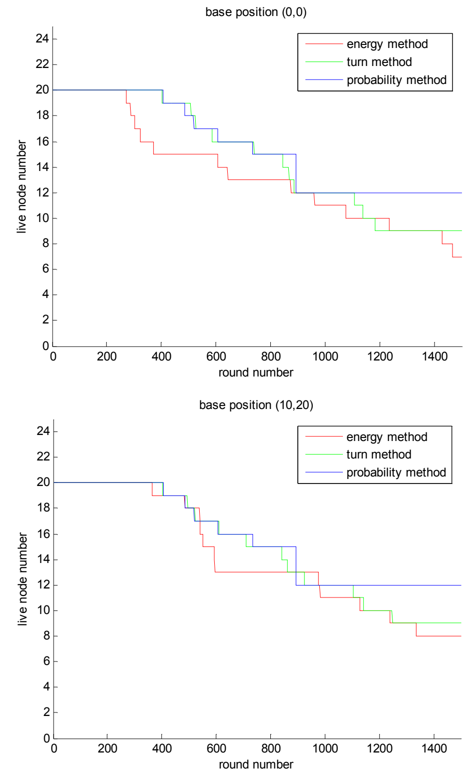
Method	Base Station Location			
	(0,0)	(10,20)	(100,0)	(100,100)
Energy Method	1029	1029	1029	1029
Turns Method	1197	1195	1196	1195
Probability Method	1204	1204	1204	1204

Table 4. Network lifetime rounds when first of the nodes died for a larger region (100×100) m^2

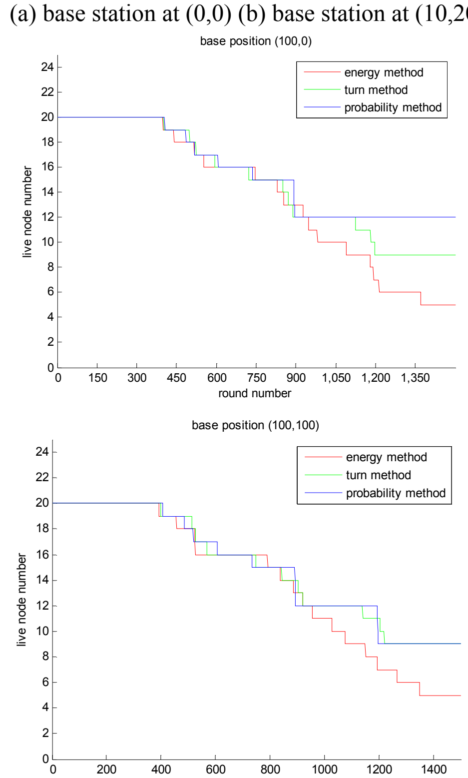
Method	Base Station Location			
	(0,0)	(50,100)	(500,0)	(500,500)
Energy Method	272	390	394	394
Turns Method	406	406	405	405
Probability Method	403	397	402	395

Table 5. Network lifetime rounds when half of the nodes died for a larger region (100×100) m^2

Method	Base Station Location			
	(0,0)	(50, 100)	(500, 0)	(500, 500)
Energy Method	1029	1029	1029	1029
Turns Method	1196	1196	1196	1196
Probability Method	1181	1226	1223	1204

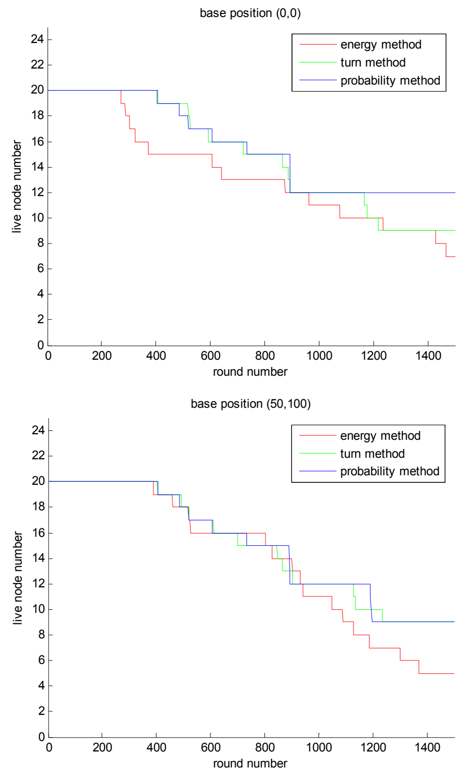


(a) base station at (0,0) (b) base station at (10,20)

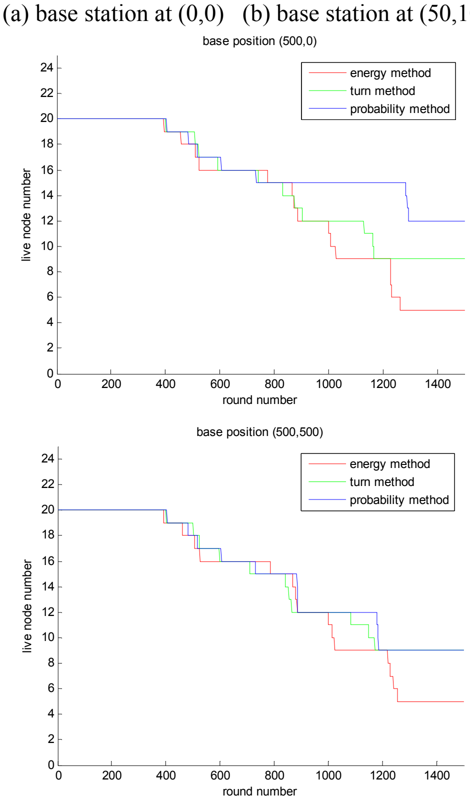


(c) base station at (100,0) (d) base station at (100,100)

Figure 2. Network lifetime comparison in a smaller region (20×20)



(a) base station at (0,0) (b) base station at (50,100)



(c) base station at (500,0) (d) base station at (500,500)

Figure 3. Network lifetime comparison in a larger region (100×100)

5. Conclusions

In this paper we proposed and evaluated a routing optimization scheme based on graph theory and PSO algorithm for multi-hop WSNs. Our algorithm synthesized the intuitionist advantages of graph theory and optimal search capability of PSO. We discussed the cluster heads election methods by maximum residual energy and in turns and by probabilities separately. The result is completely different from that in single-hop WSNs. The result shows that there is very little difference from these methods. The reason is discussed in detail.

We can conclude that the network lifetime almost has nothing to do with the base station location or the residual energy of the node. Once the topology of the network is decided, the lifetime is settled. There are two ways to improve the network lifetime. One way is to reduce the energy consumption for transmitter or receiver startup. The other way is to optimize the network topology. It is worthy to research in the future.

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