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Double Layers Clustering Algorithm Based on CPSO for Wireless Sensor Networks

Zhaoxia Wu, Youjin Nie, Shuqiang Chen, Huifang Zhang and Lifu Wang
College of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao, 066004, China

Abstract: Wireless Sensor Network (WSN) has broad prospects for development. At the same time, the limitation of node energy and non-rechargeable character of the node restrict WSN extensive application. Thus, clouds particle swarm algorithm combined with clustering method for optimizing WSN clumping process was proposed in this study. Cloud Particle Swarm Optimization (CPSO) algorithm can quickly and accurately search the optimal clustering method, double layers means that the whole network is divided into two layers of cluster structure. It realizes the balanced energy consumption and the energy conservation, avoids network black hole caused by the network energy consumption imbalances and prolongs the network life cycle. The simulation results show that the algorithm can save energy in certain application environment, balance node energy consumption and prolong the network survival cycle.

Key words: Cloud particle swarm optimization algorithm, wireless sensor networks, double layers clustering, energy balance

INTRODUCTION

Due to rapid development of the industrialization in our country, Wireless Network Sensor (WSN) is extensively applied in lots of fields. One of the bottleneck in WSN research and development is the limited and non-rechargeable energy (Sohrabi *et al*., 2000). The sensor energy consumption can be considered in two aspects. Energy conservation means saving the whole network energy to prolong the life of the network. Balancing energy consumption means equalizing all the nodes energy consumption during data transmission to avoid nodes premature death caused by the excess consumption of one or more nodes. With the research of many scholars towards the WSN energy all over the world, it has proposed many algorithms applied in WSN. Commonly, the structure of WSN includes flat routing and hierarchical structure (Al-Karaki and Kamal, 2004). In flat routing structure, the position of all the nodes are the same which means every node sends data and transmits data from other nodes. Flooding, SPIN, Gossiping and SAR are the typical routing algorithms (Chong and Kumar, 2003). These algorithms are available in small-scale networks. But in large scale networks, the energy of nodes would consume excessively because of plenty of nodes and data redundancy. In order to cover the shortage of flat routing, hierarchical routing has been developed widely. The main idea of hierarchical routing algorithm is to cluster the whole network which can be called as clustering routing algorithm. It divides the WSN into several areas according to a certain rules which are called clustering. Then it will select clustering heads in a certain ways which receives and integrates the data transmitted from the member nodes. Compared with flat routing, hierarchical routing decreases the amount of data communication to a great extent and the cluster members just need to send the data in their corresponding time slot and then be set in dormant state while there is no data sent. Thus, hierarchical routing saves the whole network energy, prolong the network lifetime. LEACH (Low Energy Adaptive Clustering Hierarchy), LEACH-C (LEACH-centralized), TEEN (Threshold Sensitive Energy-efficient Sensor Network Protocol), HEED (Hybrid Energy-efficient Distributed Clustering), PEGAGIS (Power-efficient Gathering in Sensor Information System) are the typical clustering routs (Lindsey and Raghavendra, 2002).

Although, traditional hierarchical routing is much better than flat routing algorithm, the limitation is that it just realizes single layer clustering and it can't satisfy the large-scale network in which nodes are far from each other. Recently many researchers study the clustering head selection of clustering algorithm optimization through swarm intelligence method to select optimal clustering heads and cut the communication energy consumption. Such as optimal methods based on genetic algorithm, ant colony algorithm, particle swarm algorithm. Swarm intelligence method shows a fairly good result applied to WSN, saving the energy and prolonging the network lifetime (Zhou and Liu, 2009).

Corresponding Author: Zhaoxia Wu, College of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao, 066004, China

So far, hierarchical routing communicates applying a single layer way. When the distance between nodes and clustering heads is far, energy consumption will be excessive through long distance communication. To fill up the deficiency of the method, this study proposed an algorithm with two layers which requires higher quality of speed and accuracy. This study adopts double layers clustering algorithm with optimal cloud particle swarm which is simple, fast and accurate to optimize the network energy consumption and prolong the whole network lifetime.

WSN ENERGY CONSUMPTION MODEL

According to the character of WSN, this study adopts first-order energy consumption model (Zhang and Shen, 2010; Wang *et al*., 2010). This model controls the transmission power to minimize energy for transmission. The energy spent for transmission of a k data over distance d is:

$$E_{Tx}(k,\ d)=\begin{cases}E_{elec}\times k+E_{fs}\times k\times d^2 & d<d_0\\ E_{elec}\times k+E_{mp}\times k\times d^4 & d\ge d_0\end{cases} \quad (1)$$

where, d_0 is the distance threshold, E_{elec} is the energy of transmitting circuit loss, E_{fs}, E_{mp} depends on the transmitter amplifier we use. The energy consumption for receiving k data is:

$$E_{Rx}(k) = k\times E_{elec} \quad (2)$$

The energy consumption for fusing k data is:

$$E_M = k\times E_D \quad (3)$$

where, E_D is the energy consumption for fusing each bit data.

CLOUD PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle Swarm Optimization (PSO) algorithm is a typical swarm intelligence optimal algorithm. Its available solution is abstracted into massless, sizeless micro particles with the message of speed and position in practice (Ling *et al*., 2006). Additionally, fitness function in this algorithm is defined to judge the performance of research results according to actual situation. Each particle calculates its fitness value according to fitness function. Particle memorizes the so-far personal best position (pbest) and global best position (gbest). Meantime, it will determine next searching direction and distance with corresponding updating method according to its position and speed.

Assume the dimension of particle is d, after both the gbest and pbest are determined, velocity and position are updated with following expression:

$$v_{id}(t+1) = wv_{id}(t)+c_1r_1\ [p_{id}-x_{id}(t)]+c_2r_2\ [p_{gd}-x_{id}(t)] \quad (4)$$

$$x_{id}(t+1) = x_{id}(t)+v_{id}(t+1) \quad (5)$$

where, w is inertial weight, reflecting the amount of succession from father particle; c_1 and c_2 are study factor, reflecting the ability of self-study and swarm-study, r_1 and r_1 are random uniformly distributed in [0,1].

To avoid particles leaving the searching area, limitation for the velocity of particle search is necessary, the adjusted velocity expression is:

$$\begin{cases}v_{id}=v_{max}, & v_{id}>v_{max}\\ v_{id}=-v_{max}, & v_{id}\le v_{max}\end{cases} \quad (6)$$

In the particle algorithm, larger value of w can enlarge the particle search range which is beneficial to the searching for best value globally. While smaller w can speed up the algorithm convergence which is beneficial to the searching for best value locally. So, this study introduces CPSO, dividing the swarm into three parts and each part uses different inertial weight to update the particle velocity and position messages (Zhang *et al*., 2011; Gao *et al*., 2010).

Assume f_i^k is the fitness of particle i after k times iteration; The average fitness of all the particles is:

$$f_{avg}^k=\frac{1}{N}\sum_{i=1}^{N}f_i^k$$

the optimal fitness is f^k_{best}, particles whose fitness is greater than f^k_{avg} combine and calculate their average fitness f^1_{avg}, particles greater than f^k_{avg} combine and calculate their average fitness f^2_{avg}. In CPSO algorithm, with different particle fitness, we can range the inertial weight combined with the cloud model theory to improve the selection strategy (Xia *et al*., 2011). The specific methods are listed as follows:

- When $f_i^k>f^1_{avg}$, the particles are near the best solution, the system should speed up local convergence but not to search globally
- When $f^1_{avg}>f_i^k>f^2_{avg}$, the particles are modified with cloud model. The particle best value is the expected value of cloud model $Ex = f^k_{best}$, particle entropy is: $En = (f^1_{avg}-f^k_{best})$, particle super entropy value is:

He-En/c_2, then w is:

$$w = 0.9 - 0.5e^{\frac{-(f_i^k - Ex)^2}{2(En^1)^2}}$$

where, En^1 = normrnd (En, He), c_1, c_2 are control parameters, normrnd is normal random number generator, $c_1 = 2$, $c_2 = 2$

- When $f_i^k > f^2_{avg}$, these particles are far from the swarm, now we need to focus on enlarging searching scope, w is set as 0.9

In WSN, we care about the best value in particles. So we introduce the crossover mutation in the first part, taking p as the crossover probability and combine the neighbor particles into new particle, the expressions are as follows:

$$x_i^1 = p.x^1_{i-1} + (1-p).x^2_{i-1} \tag{7}$$

$$x_i^2 = p.x^2_{i-1} + (1-p).x^1_{i-1} \tag{8}$$

$$v_i^1 = \frac{v^1_{i-1} + v^2_{i-1}}{\left|v^1_{i-1} + v^2_{i-1}\right|}\left|v^1_{i-1}\right| \tag{9}$$

$$v_i^2 = \frac{v^1_{i-1} + v^2_{i-1}}{\left|v^1_{i-1} + v^2_{i-1}\right|}\left|v^2_{i-1}\right| \tag{10}$$

DOUBLE LAYERS CLUSTERING ALGORITHM BASED ON CPSO

Double layers clustering algorithm is proposed based on clustering routing algorithm which is called single layer clustering. In double layers clustering, the cluster will be clustered again in each cluster after the whole network is clustered. Corresponding members will send data to the selected secondary clustering heads which will send the fused data to its corresponding first clustering heads. After that, all the first clustering heads will fuse and send the data to base station. Thus the whole network is finished with double layers clustering and node data transmission. The hierarchical structure shows as follows in Fig. 1.

Compared with single clustering algorithm, the purpose of double clustering is to add the secondary clustering heads between first clustering heads based on first clustering to shorten the distance between the first clustering heads and cluster members. That could avoid over consumption of long distance data transmission. Then we will analyze the situation of saving energy by increasing secondary clustering heads.

The analysis of energy of nodes is shown in Fig. 2. In single layer clustering, nodes will send data to first cluster heads directly through the distance d_1. While in double layers clustering, nodes will only send data to secondary cluster heads through the distance d_2. Then the secondary cluster heads fuse the all the data including its own to send them to first cluster heads. Thus the energy for transmission of nodes is decreased obviously. We will describe this problem through energy expression (1) and (3). Compare the single and double layers clustering algorithm, the data quantity that will be sent is the same which means the part $E_{elec} \times k$ is fixed.

No matter $d<d_0$ or $d \geq d_0$, energy for data transmission $E_{fs} \times k \times d_1^2 - E_{fs} \times k \times d_2^2$ or $E_{fs} \times k \times d_1^4 - E_{fs} \times k \times d_2^4$ are always greater than zero. So, when the node density is high which means d_1 and d_2 are closed, then there is no difference between single and double layers algorithm. While the node density is low which means d_1 and d_2 are quite different, then the character of saving energy of double layers algorithm is obviously better than single layer algorithm. Therefore, double layers clustering algorithm can save energy efficiently and it's more available for large range environment.

During double layers clustering, the first and secondary clustering heads are selected with CPSO optimal algorithm. High-speed, accuracy and variable inertial weight of CPSO ensures the large scale search which ensures optimal clustering heads. In CPSO algorithm, each particle with d dimension is like an array with one row and one column. In practice, CPSO sets each dimension of a particle as a node and then the particle will

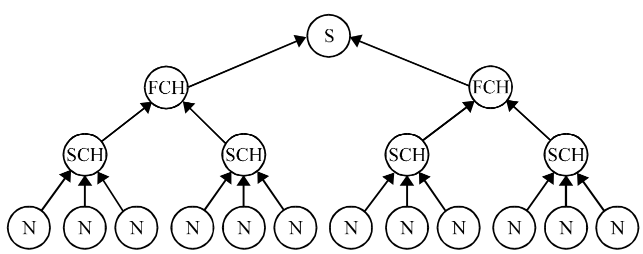

Fig. 1: WSN hierarchical structure of CPSO; S: Sink node, FCH: First clustering head, SCH: Secondary clustering head, N: Cluster members

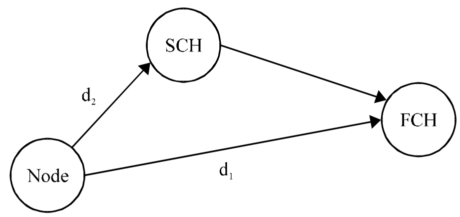

Fig. 2: Distance between node and first and second cluster heads, FCH: First clustering head, SCH: Secondary clustering head

be an array with d dimension. Thus the node corresponding to optimal particle is clustering head with continuously updating in practice. CPSO will be applied in the WSN clustering head selection because all the particles dimension are determined by the number of selected clustering heads.

In CPSO, particle determines the next updated parameter according to its own fitness. Fitness function is set through certain situation. In WSN, to minimize the energy consumption, the rule of clustering head selection should be combined with compact clustering structure, energy of the selected clustering head and the distance between clustering head and the base station which makes fitness function essential. For a sensor network with N nodes and K predetermined number of clusters, there should be C_N^K clustering ways. Select K clustering heads in N nodes and minimize the fitness of those clustering heads. Define the target function as follows (Su and Huang, 2011):

$$\text{cost} = a_1 f_1 + a_2 f_2 + a_3 f_3 \tag{11}$$

$$f_1 = \max_{k=1,2,\dots,K} \left\{ \sum_{\forall n_i \in C_{p,k}} d(n_i,\ CH_{p,k}) / |C_{p,k}| \right\} \tag{12}$$

$$f_2 = \sum_{i=1}^{N} E(n_i) / \sum_{k=1}^{K} E(CH_{p,k}) \tag{13}$$

$$f_3 = \max_{k=1,2,\dots,K} \{ d(BS,\ CH_{p,k}) / d(BS,\ NC) \} \tag{14}$$

where, f_1 is clustering geometry compaction, $|C_{p,k}|$ is the number of nodes that belong to cluster C_k of particle p. f_2 is the ratio of total initial energy of all nodes. f_3 is the distance relationship of cluster head and base station and network geometry center. a_1, a_2, a_3 are respective the user-defined constant used to weigh the contribution of the three evaluation factors.

The procedure of double layers clustering applying CPSO optimal algorithm is listed as follows:

- First clustering head selection procedure:

Step 1 : Distribute certain number of sensor nodes in certain area randomly and initialize each node with equal energy

Step 2 : Select K nodes to initialize a particle randomly and circulate it for Q times. Here K clustering heads will be selected, so Q particles with K dimension are supposed to be generated

Step 3 : Calculate each particle's fitness and obtain pbest and gbest

Step 4 : Update particle swarm according to the expression and calculate fitness. If fitness is less than pbest, update pbest. If fitness is less than gbest, update gbest. Circulate step 4 till the maximum number of iterations is reached

Step 5 : Set the node corresponded to swarm gbest particle as first clustering head. Non-clustering heads select their own clustering heads according to the distance

- Secondary clustering head selection procedure:

Step 6 : Select a cluster and assume the clustering head as new base station, with the geometry center as new network center

Step 7 : V cluster members are supposed to act as secondary clustering heads. So q particles with k dimension are generated. Select v cluster members to initialize the particle randomly in the cluster and circulating for q times

Step 8 : Calculate the fitness of each particle for pbest and gbest

Step 9 : Update particle swarm and calculate fitness according to updating expression. If fitness is less than pbest, update pbest. If it is less than gbest, update gbest. Circulate step 9 till the maximum number of iterations is reached

Step 10 : Set the node corresponded to swarm gbest particle as secondary clustering head. Non-clustering heads select their own secondary clustering heads according to the distance

Step 11 : Repeat from step 6 till the secondary clustering process is finished in K first clusters

Step 12 : Transmit data for *t* times according to the selected first and secondary clustering heads and energy consumption model

Step 13 : Repeat from step 4 and reselect first and secondary clustering heads. Run the communication till the maximum number of execution is reached

SIMULATIONS AND ANALYSIS

This study simulated through MATLAB. The performance priority of double layers clustering algorithm was compared with single layer clustering based on PSO, double layers clustering based on PSO, single layer clustering based on CPSO and double layers clustering based on CPSO. We simulated and analyzed the network life time of the four algorithms.

We ran the simulations for 100 nodes in 500×500 m network area. The base station was set at (250, 750 m) where it would be applied more generally outside of the network area. Data package for each transmission was 2000 bits. Initial energy was equally 1.5 J. Parameter of energy consumption model was: E_{elec} = 50 nJ/bit, E_{fs} = 10 pJ/bit/m^2, E_{mp} = 0.0013 pJ/bit/m^4, E_D = 5 nJ/bit, transmission distance was d_0 = sqrt(Efs/Emp).

In PSO single layer clustering, number of particle was Q = 20, the number of selected clustering heads was 5% of all the nodes, maximum iteration number was P = 10, updating parameter of particle was w = 0.8, c_1 = 2, c_2 = 2. a_1 = 0.4, a_2 = 0.4. Maximum velocity for particle search was v_{max} = 20.

In first cluster of PSO double layers clustering, number of particle was Q = 20, selected clustering heads accounted for 5% of the particle swarm. and P = 10. In secondary cluster, number of particle was q = 10, secondary clustering heads accounted for 20% of all the nodes and maximum iteration number was p = 20. Updating parameter was c_1 = 2, c_2 = 2. a_1 = 0.4, a_2 = 0.4. Maximum velocity for particle search was v_{max} = 20.

In CPSO single clustering, number of particle was Q = 20, selected clustering heads was 5% of all the nodes, maximum iteration number was P = 10, updating parameter of particle was w = 0.8, c_1 = 2, c_2 = 2. Inertial weight w was determined by CPSO inertial weight method. a_1 = 0.4, a_2 = 0.4, a_3 = 0.2. Maximum velocity for particle search was v_{max} = 20.

In first cluster of CPSO double clustering, number of particle was Q = 20, selected clustering heads accounted for 5% of the particle swarm, P = 10. In secondary cluster, number of particle was Q = 10, secondary clustering heads accounted for 20% of all the nodes and maximum iteration number was P = 20. Updating parameter was c_1 = 2, c_2 = 2. Inertial weight w was determined by CPSO inertial weight method. a_1 = 0.4, a_2 = 0.4, a_3 = 0.2. Maximum velocity for particle search was v_{max} = 20.

To clarify that CPSO double layers clustering algorithm can prolong the network life time effectively, we ran the simulations of the life time curves of the four algorithms in which it performed clustering for 2000 times. The network executed for 3 times after each clustering.

In Fig. 3-5, "PSO-SLC", "PSO-DLC", "CPSO-SLC" and "CPSO-DLC", respectively stands for "particle swarm optimization-single layer clustering", "particle swarm optimization-double layers clustering", "cloud particle swarm optimization-single layer clustering" "cloud particle swarm optimization-double layers clustering".

Figure 3 shows that CPSO double layers clustering algorithm prolongs the lifetime of network obviously. When 30% of the nodes are dead, the transmission doesn't work efficiently and the lifetime of CPSO double layers clustering is, respectively 4.52, 1.27 and 4.88 times longer than that of PSO single clustering, PSO double layers clustering and CPSO single layer clustering, from which we drew the conclusion that CPSO double layers clustering shows an obvious superiority.

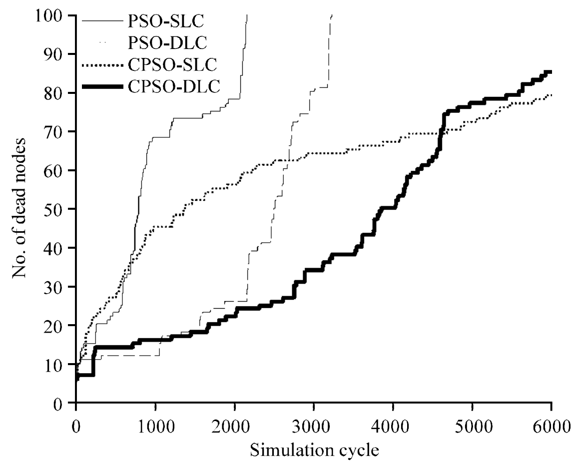

Fig. 3: Number of dead nodes over time with simulation cycle

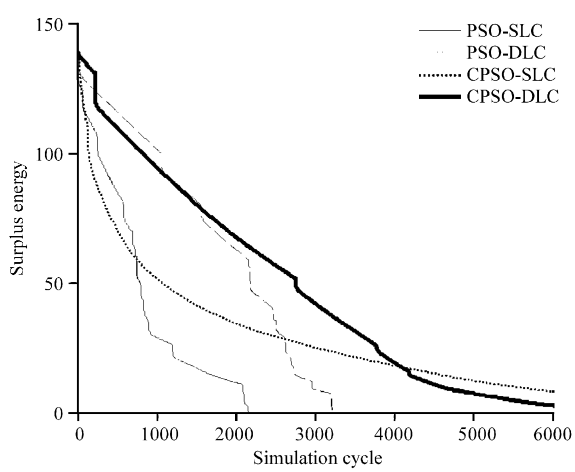

Fig. 4: Surplus energy of whole network over time with simulation cycle

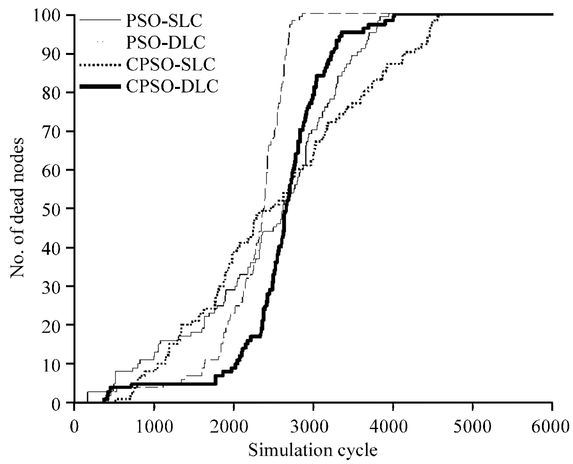

Fig. 5: Number of dead nodes over time with simulation cycle

Figure 4 give the simulation results of total network energy of nodes alive over time with simulation cycle of the four algorithms.

Figure 4 illustrates that our proposed algorithm can balance the energy consumption significantly and save total network energy.

As the simulation results show above, double layers clustering is applied to large scale spaces. Double layers clustering can save little energy in a small area, showing an inapparent priority which is shown in Fig. 5 with 100 nodes distributed in 100×100 m network. In order to shorten simulation time, we change the initial energy of nodes to 0.5 J.

Figure 5 is the curves of dead nodes changing with simulation cycle of the four algorithms. The plot clearly indicates the effectiveness and accuracy of the proposed algorithm in prolonging lifetime of network. In small-scale of range, the performance of double layers clustering algorithm is the same as others.

CONCLUSION

Energy limitation is the major factor in WSN application. Therefore, the goal of routing design is saving energy and prolonging the life time of network. This paper has achieved the goal of reducing energy consumption from two aspects. On one hand, double layers clustering algorithm decreases the excess energy consumption of data transmission through long distance to economize total energy of network. On the other hand, we have realized the variable inertial weight which ensures the large search range and avoids premature local optimization. Hence, the network can find a set of optimal nodes to act as clustering heads to balance the energy consumption in network, avoiding premature death of local nodes. Therefore, CPSO-based double layers clustering algorithm shows a good performance in WSN application. As stated previously, CPSO-based double layers clustering algorithm is available for large-scale area. Even in small environment, the performance of the proposed algorithm is closed to other algorithm. In a word, double layers clustering algorithm based on CPSO promotes a further application and development of WSN.

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