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Design of cluster-based routing protocol targeted at low-energy consumption of monitoring area based on self-organizing map neural network and artificial immune algorithm

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Abstract. To maximally increase the life cycle of wireless sensor network of a monitoring area, we propose a cluster-based routing protocol (CBRP) targeted at low-energy consumption based on Low-Energy Adaptive Clustering Hierarchy (LEACH) Protocol. First, energy and node density are considered in cluster head election. When the cluster heads are determined, Self-Organizing Map (SOM) neural network is used to cluster nodes, to make clusters more homogeneous. Inter-cluster multi-hop transmission is adopted. Further, we define an artificial immune algorithm based on optimization of inter-cluster multi-hop routing. Optimal routing from cluster heads to base stations is acquired by population encoding, crossover, mutation, and immune selection. Simulation experiment demonstrates that CBRP based on SOM neural network and artificial immune algorithm achieves improvement of LEACH protocol, prominently enhances load balance of nodes, increases network life cycle, and thus has an obvious superiority.

Key words. Artificial Immune Algorithm, Protocol, Low Energy Consumption, Neural Network.

1. Introduction

Sensor nodes in a Wireless Sensor Network (WSN) [1, 2] are usually powered by batteries, whose energy is hard to be recharged. To reduce energy consumption of sensors in a monitoring area so as to extend the life cycle of network is an urgent issue to be solved for wireless sensor network.

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Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol [3] is a classic cluster-based routing protocol (CBRP). However, node energy consumption is not considered in the process of cluster head selection in LEACH, which leads to unbalanced energy consumption among nodes. HEED[4], TEEN[5], and PEGASIS[6] are all improvements of LEACH protocol, but the issues of unbalanced energy consumption and high cost of clustering still remain.

Reference [7] utilizes inhomogeneous competing zones to construct clusters of unequal size, to make size of a cluster near a convergent point far less than that far from a convergent point, thus extending the length of existence of a network. Reference [8] first randomly generates candidate cluster heads, and then groups all nodes by competition based on distance; in subsequent cluster head election, it considers remaining energy of nodes and cost of communication within a cluster. Reference [9] presents a clustering scheme of sensor nodes by utilizing multiple particle swarms to optimize learning and accelerate clustering convergence, which overcomes the issue of sensitivity to choice of initial cluster centers.

The previous studies have improved balance of node energy consumption to some extent and contributed in increasing network life cycle. Building upon previous results, this study uses SOM in clustering. After clusters are formed, all nodes transmit data to their cluster heads via single-hop communication, while multi-hop communication is adopted for data transmission from cluster heads to convergent nodes. The optimized routing is acquired by an artificial immune algorithm.

2. LEACH Protocol

The basic idea of LEACH protocol is to randomly select cluster head nodes and distribute energy load of a network to each node, thus reducing energy consumption and extending life cycle of a network. Execution of LEACH protocol is described by "rounds", each of which can be divided into phases of cluster formation and data transmission.

In the phase of cluster formation, each sensor node is distributed with a random number between 0 and 1. When the random number of a node is less than a threshold value, this node becomes a cluster head. Calculation formula for the threshold value is shown in Formula (1):

$$T(k) = \begin{cases} \frac{p}{1-p*\lceil rmod(/p)\rceil} & k \in G \\ 0 & k \notin G \end{cases} \tag{1}$$

Where p represents probability of a sensor node to become a cluster head; r represents the current number of rounds; G indicates the set of nodes that have not been a cluster head.

In LEACH protocol, nodes in a network form clusters by self-organization, which leads to the following defects:

(1) Since cluster heads are generated randomly, homogeneity of cluster heads distribution is not guaranteed. In addition, factors such as distance for transmission and remaining energy of a node are not considered, which results in unbalanced

energy consumption.

(2) Single-hop communication is adopted for data transmission from cluster head nodes to base stations, leading to higher energy consumption for data transmission from cluster head nodes farther from a base station.

3. Clustering based on SOM

3.1. Selection of Cluster Head

In the process of cluster head selection, remaining energy of a node and density of surrounding nodes are considered on the basis of LEACH protocol. The calculation formula for threshold value is given by Formula (2):

$$T(k) = \begin{cases} \frac{p*E_{remain}}{1-p*\lceil rmod(/p)\rceil * E_0 * S} & k \in G \\ 0 & k \notin G \end{cases} \tag{2}$$

Where E_{remain} represents the remaining energy of a node; E_0 represents the initial energy of a node; S represents density of surrounding nodes of a candidate node. The greater the density, the less the threshold.

3.2. Clustering Based on SOM

Self-Organizing Map (SOM) [10], proposed by Kohonen, realizes unsupervised, self-organized learning by competition, cooperation and weight adjustment, containing input layer and output layer, as shown in Figure 1.

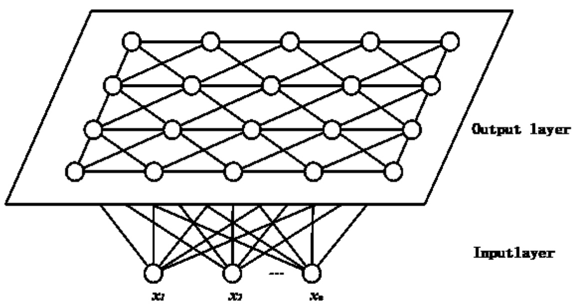


Fig. 1. SOM Neural Network

As shown in Figure 1, all nodes in both input and output layers are connected based on weight values. Neurons in the output layer compete for opportunities of response to the input pattern. This makes weight relevant to winning neurons develops toward a direction that is advantageous with competition.

By clustering using SOM neural network, the number of input neurons is the number of dimensions of coordinates of sensor nodes in the monitoring area. The coordinates of sensor nodes can be calculated using RSSI values of cluster head messages received. The number of output neurons is just the number of cluster heads winning the competition. The algorithm is as follows:

Algorithm 1: Clustering Algorithm based on SOM

Initialization: n - number of input neurons n, m - number of output neurons;

Step 1: The following parameters are set: current number of iteration t=1, the maximum number of iteration T, learning rate factor $\psi(1)$, radius of neighborhood $N(1)$, and initial weight $W_{ij}(1)$.

Step 2: All initial weight values $W_{ij}(1)$ and sample data are normalized.

Step 3: Euclidean distance between the coordinate of each sensor, corresponding to a sample datum, and its output neuron, i. e., the cluster head, is calculated.

$$D_{ij}(t) = \sum_{i}^{n}(w_{ij}(t) - x_i(t))^2 \;\; j = 1, 2, ..., m \tag{3}$$

Step 4: Neurons with the minimum $D_{ij}(t)$ (j=1,2,...,m) are treated as winning neurons;

Step 5: Neurons within the neighborhood of winning neuron nodes are adjusted as shown below:

$$w_{ij}(t+1) = w_{ij}(t) + \psi(t)(x_i - w_{ij}(t)) \tag{4}$$

Step 6: Neighborhood and learning rate of winning neurons are updated according to Formulas (5) and(6).

$$\psi(t) = \psi(1)(1 - t/T) \tag{5}$$

$$N(t) = N(1)(1 - t/T) \tag{6}$$

Step 7: If learning rate $\psi(t)$ falls to zero or the current number of iteration reaches maximum T, the algorithm terminates, or else t=t+1, and return to Step 2.

4. Acquiring Multi-Hop Path of a Cluster Head using Artificial Immune Algorithm

Data transmission starts after clustering finishes. A cluster head allocates time slots for each node within the cluster. Within the time slot allocated, a node transmits data to the cluster head by single-hop communication. After data fusion, a cluster head transmits data to a convergent node. Multi-hop communication is adopted for data transmission between cluster heads. In this study, the multi-hop routing between cluster heads is optimized employing artificial immune system.

4.1. Artificial Immune Algorithm

Artificial immune algorithm is a bionic algorithm developed from somatic cell theory and network theory. It realizes functions similar to a biological immune system, such as antigen recognition, cell differentiation, memory and autoregulation.

As a highly distributed self-adaptive learning system, it has become a focus in the application field of artificial intelligence [11].

Artificial immune algorithm treats an issue to be addressed as an antigen, and extracts characteristic information, namely, vaccines, based on experience. Solutions, namely individuals, are obtained according to the vaccines. Finally, the next generation is generated by operating individuals using vaccine operators.

4.2. Generation of Multi-Hop Path using Artificial Immune Algorithm

To establish a multi-hop path from a cluster head to a convergent node using artificial immune algorithm, the main steps include population initialization, selection of vaccines and fitness function, and immune operation. Detail of the algorithm is as follows:

Algorithm 2: Algorithm of Acquiring Multi-Hop Path

Initialization: population size M, number of iteration T, crossover probabilityp_c, variation probabilityp_m, vaccination probability p_f.

Step 1: Binary coding is used to encode an individual. The length of code is the sum of number of cluster head nodes and number of convergent nodes. "1" indicates a node is along the path, while "0" indicates a node is not along the path. An antigen set with size of M is randomly generated.

Step 2: The optimal path to be searched is that to the antigen. Affinity between an antibody and an antigen can be calculated according to Formula (7):

$$fit(v) = \frac{E_{remain}^{avg}}{hop(v, \sin k)} \tag{7}$$

Where v is a source node; sink is a convergent node; $hop(v, \sin k)$ represents number of hops between the source node v and the target node sink; E_{remain}^{avg} is the average remaining energy of all nodes along the path. An individual with the maximum affinity is selected, with some of its genes truncated as a vaccine.

Step 3: Crossover and mutation of the current population are carried out based on probabilities p_c and p_m.

Step 4: Vaccination of the current population is carried out. Vaccinated individuals are detected by immunoassay. If affinity between an individual and its antigen is less than that of the parent generation, then the individual will be replaced by its parent individual. On the other hand, if affinity between an individual and its antigen is greater than that of the parent generation, then simulated annealing is adopted in choosing the individual with a probability of p_f to join a new parent population. The procedure is shown below:

$$p_f(x_i) = \frac{e^{fit(x_i)/T_k}}{\sum_{i=1}^{n} e^{fit(x_i)/T_k}} \tag{8}$$

Where $fit(x_i)$ indicates the affinity between individual x_i and its antigen, and $\{T_k\}$ indicates a temperature control sequence approaching zero.

Step 5: t=t+1, judge if the current number of iteration reaches the maximum value. If yes, the algorithm terminates, with the optimal individual outputted; or else jump to Step 2 to continue iteration.

5. Simulation Experiment

Matlab is used in simulation experiment in the study. We use an energy model similar to Reference [12]. Configuration parameters of the experiment are shown below:

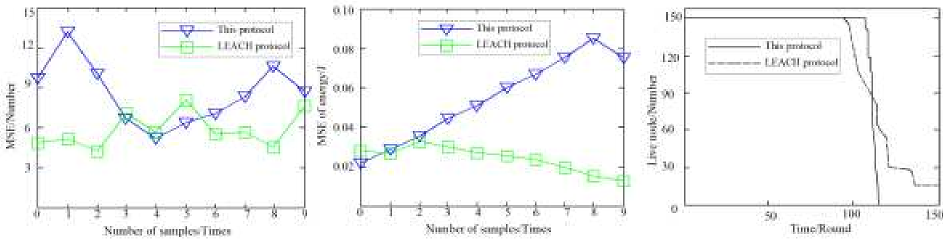
Table 1. Configuration Parameters of Experiment

Parameter	**Value**
Monitoring area	(0,0)∼(100,100)m
Initial energy	1J
Number of nodes	100
Coordinate of Sink	(0,0) m
ε_{fs}	20pJ/bit*m^2
ε_{mp}	0.004pJ/bit*m^4
Energy consumption for transmitting/receiving circuits E_{elec}	50nJ/bit
Data fusion/Energy consumptionE_{da}	20nJ/bit
Size of data packet	3500bit

In this study, SOM neural network is used for clustering, to make the clustering results as homogeneous as possible, and to keep the energy for a node to transmit data to a cluster head as small as possible. To verify this, clustering results in the execution of algorithm under stable operation of network are analyzed, as shown in Figure 2.

As can be seen from Figure 2, the mean square error (MSE) of number of clusters based on LEACH protocol changes hugely by 5 - 12. The reason can be derived from the randomness in selection of cluster head based on LEACH protocol. In addition, a node applies in a cluster merely according to intensity of signal received from the cluster head node, which makes size of a cluster uncontrollable. However, relatively stable results can be obtained using the method of this study. According to our results, the mean square error is between 5 - 7. Such improvement is made possible because of the employment of SOM neural network, which guarantees homogeneity of clusters.

MSE of energy of all nodes in the network is simulated, and compared with the result based on LEACH protocol, as shown in Figure 2.



(a)Variation curve of MSE of number of clusters **(b) Variation curve of MSE of node energy**
(c)Variation curve of live node

Fig. 2. Experiments result

As can be seen in Figure 2, MSE of energy using protocol of this study is less compared with that using LEACH protocol, which indicates uniform energy consumption and better load balance using method of this study.

The life cycle of network is simulated and compared with that of LEACH protocol, with the results shown in Figure 2.

As shown in Figure 2, the protocol proposed in this study has maintained running for about 120 rounds, while LEACH protocol has maintained running for about 100 rounds, not mentioning existence of some idle nodes in late stage. The superiority of our protocol stems from employment of SOM neural network in clustering as well as optimization of multi-hop routing of cluster head using artificial immune algorithm. By doing so, energy consumptions within and beyond a cluster are balanced, which stabilizes a network for longer time.

6. Conclusion

In this study, a network protocol for monitoring area based on SOM neural network and artificial immune algorithm is proposed on the basis of LEACH protocol. The purpose of this protocol is to solve the existing issue of unbalanced load under LEACH protocol that can lead to shortening of network life cycle. In our protocol, SOM neural network is used for clustering based on an improved method to select cluster head, which lowers energy consumption during data transmission within a cluster. In the meantime, artificial immune algorithm is used to optimize inter-cluster multi-hop routing, with consideration of length of routing path and node energy, so that a cluster head is guaranteed to transmit data along the optimized path. Simulation experiment shows our protocol has significant advantages in aspects of homogeneity of clusters, load balance, and network operation, compared with LEACH protocol.

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