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RBF-based cluster-head selection for wireless sensor networks

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Abstract: The radial basis function (RBF), a kind of neural networks algorithm, is adopted to select cluster-heads. It has many advantages such as simple parallel distributed computation, distributed storage, and fast learning. Four factors related to a node becoming a cluster-head are drawn by analysis, which are energy (energy available in each node), number (the number of neighboring nodes), centrality (a value to classify the nodes based on the proximity how central the node is to the cluster), and location (the distance between the base station and the node). The factors are as input variables of neural networks and the output variable is suitability that is the degree of a node becoming a cluster head. A group of cluster-heads are selected according to the size of network. Then the base station broadcasts a message containing the list of cluster-heads' IDs to all nodes. After that, each cluster-head announces its new status to all its neighbors and sets up a new cluster. If a node around it receives the message, it registers itself to be a member of the cluster. After identifying all the members, the cluster-head manages them and carries out data aggregation in each cluster. Thus data flowing in the network decreases and energy consumption of nodes decreases accordingly. Experimental results show that, compared with other algorithms, the proposed algorithm can significantly increase the lifetime of the sensor network.

Key words: sensor networks; radial basis function; cluster-head selection

Wireless sensor networks (WSNs) consist of numerous microsensor nodes that can be connected via a wireless network. WSNs represent a new paradigm for extracting data from the environment and enable the reliable monitoring for a variety of environments for applications that include precision farming, surveillance, machine failure diagnosis, and chemical/biological detection[1-4]. The WSNs have typical characteristics such as limited power, memory and computational capabilities. The lifetime of a sensor field is mainly determined by the nodes battery lifetime. Therefore, the lifetime of a sensor field is influenced by the usage pattern of the nodes batteries. So the energy supply of the sensor nodes is one of the main constraints in the design of this type of network[4]. However, reducing data flowing over the network is an effective way of decreasing node power consumption. So in the procedure of collecting and transmitting information, in-network processing is made as much as possible. Data aggregation and in-network processing techniques have been investigated recently as efficient approaches to achieve significant energy savings in WSNs by combing data coming from different sensor nodes at some aggregation points, eliminating redundancy, and minimizing the number of transmissions before forwarding data to the base station[3-4].

We compare our approach with a previously proposed popular cluster-head selection technique called low energy adaptive cluster hierarchy (LEACH)[4] on the aspects of load balance ability and network lifetime. Simulation results show that the performance of the system is improved.

1 Related Work

Routing protocols for sensor networks can be divided into two kinds: address-centric protocol (Each source independently sends data along the shortest path to sink) and data-centric protocol (The sources send data to the sink, but routing nodes can look at the content of the data and perform aggregation on multiple input packets)[1]. Data aggregation aims at data-centric protocols, which have been forward as an essential paradigm for wireless routing in sensor networks[3-4]. The idea is to combine the data coming form different sources to eliminate redundancy, minimize the number of transmissions and thus save energy. However, selection of cluster-head is the key to data aggregation.

A number of cluster-head selection methods for

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data aggregation in WSNs have been developed. One of the popular cluster-head selection techniques is called LEACH[4]. There are several disadvantages for selecting the cluster-head by this method using only local information in the nodes such as the two selected cluster-heads probably in close vicinity of each other increasing the overall energy depleted in the network, and probably the selected node located near the edge of the network[3]. The directed diffusion method sets up gradients to collect data using some reinforced paths[5]. In Ref. [6], each node calculates its distance to the area centroid, which recommends nodes closing to the area centroid and not the nodes that are central to a particular cluster. Thus when data is transmitted to the selected node, it leads to a higher overall energy consumption. Cluster-head selection using fuzzy logic for WSNs is proposed in Ref. [3]. This method requires all the categories be listed and stored in memory beforehand.

In this paper, we propose a fault-tolerant, distributed, energy-efficient data aggregation algorithm based on neural networks. The use of neural networks has the following advantages. First, once the structure and connection weights of the neural networks are known, the decision of being cluster-head is made in real time. Secondly, noise and sensors disturbance are less sensitive to the neural network, and can be easily filtered. Thirdly, the network delays are easily handled by robust neural networks so that the cluster heads are easily selected and the data aggregation is implemented by the selected cluster heads. Consequently, the lifetime of WSNs is increased by the reduction of data flow via data aggregation.

2 System Model

Consider a WSN with a base station and many homogeneous and energy-constrained sensor nodes randomly deployed in the sensor field. All the nodes are equipped with a low-power global positioning system (GPS) receiver. We assume that each node is connected to the network within its maximum power. We also assume that omni-directional antennas are used.

In our approach the cluster-heads are dynamically selected by the base station in each round based on four factors: their locations, their energy levels, the number of neighboring nodes and their proximity to the cluster heads.

During the initial network setup phase, each node floods its location information and energy level to the base station. The base station puts the acquired information into the trained neural network, to produce, for each node, a value on which the decision of being a cluster-head is based. The architecture of WSNs is shown in Fig. 1.

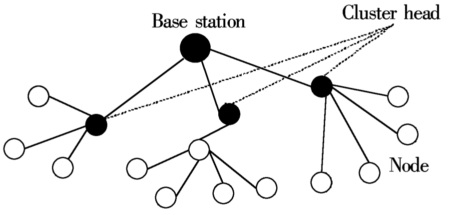

Fig. 1 Architecture of WSNs

In our opinion a central control algorithm in the base station will produce better cluster-heads since the base station has the global knowledge about the network. Moreover, base station has sufficient power, memory and storage. As mentioned earlier, we assume that the nodes are fixed, thus sending the location information during the initial setup phase is sufficient. So in this way energy consumption is little, which is spent to transmit location information of all the nodes to the base station.

The radio model we use is similar to Ref. [4] with $E_{\mathrm{elec}} = 50$ nJ/bit as the energy dissipated by the transceiver circuit and $\varepsilon_{\mathrm{amp}} = 100$ pJ/(bit·m^2) as the energy dissipation of the transmission amplifier.

The energy expended during transmission and reception for a k-bit message to a distance d between the transmitter and the receiver node is given by

$$E_{\mathrm{Tx}}(k, d) = E_{\mathrm{elec}}k + \varepsilon_{\mathrm{amp}}kd^{\lambda} \tag{1}$$

$$E_{\mathrm{Rx}}(k) = E_{\mathrm{elec}}k \tag{2}$$

where $\lambda \geqslant 2$ is the path loss exponent.

We use the access model used in Ref. [4]. Assuming r is the reception range of a node. If the distance between node l and m is not greater than r, and

$$d_{l,m} \leqslant r \tag{3}$$

the transmission is successful.

If the distance between nodes n and m is greater than r, and

$$d_{n,m} > r \tag{4}$$

here we consider relay transmission. And the transmission is also successful. In our model, the channel contention is not considered.

3 Radial Basis Function (RBF) Network

Several models of artificial neural networks have been proposed such as the multi-layer perception (MLP), self-organizing maps (SOMs), the adaptive resonance theory (ART), and the radial basis function (RBF). We choose the RBF for high mapping accuracy and efficiency.

Fig. 2 shows an RBF network with an input layer, a hidden layer, and an output layer. The transfer function of RBF ($f_1(\cdot)$ and $f_2(\cdot)$) is Gauss function. In this paper, RBF is adopted for the hidden layer, but in the output layer a linear function ($E_1(\cdot)$) is used. So the relation between input vector $\boldsymbol{X}$ and output vector $\boldsymbol{Y}$ is expressed as[7]

$$\boldsymbol{Y} = \sum_{i=1}^{N_1} w_i^{(2)} (\sqrt{2\pi}\sigma^{(1)})^{-1} \exp\left(\frac{\| \boldsymbol{X} - \boldsymbol{W}_i^{(1)} \|^2}{2(\sigma_i^{(1)})^2}\right) \tag{5}$$

where $\boldsymbol{W}_i$ is the weight vector. The weights are determined from a set of examples through the training process. The training samples are the set of inputs $\boldsymbol{x}(t)$, which corresponds to the desired outputs $\boldsymbol{y}(t)$. We specify the training set by

$$\boldsymbol{Z}^N = \{[\boldsymbol{x}(t), \boldsymbol{y}(t)], t = 1, 2, \dots, N\} \tag{6}$$

The objective of training is to determine a mapping from the set of training data to the set of possible weights

$$\boldsymbol{Z}^N \to \hat{\boldsymbol{W}} \tag{7}$$

So that the network will produce predictions $\hat{\boldsymbol{y}}(t)$ as "close" to the true outputs $\boldsymbol{y}(t)$ as possible.

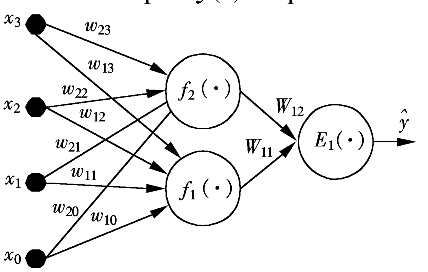

Fig. 2 Structure of RBF network

In this paper, the components of input vector $\boldsymbol{x}(t)$ = [energy, number, centrality, location] and output vector $\boldsymbol{y}(t)$ = [probability] have the following meanings.

- Energy is the energy available in each node. The more energy a node has, the higher probability it can become a cluster-head.
- Number is the number of neighboring nodes.
- Centrality is a value which classifies the nodes based on how central the node is to the cluster. To find the node centrality, the base station selects each node and calculates the sum of the squared distances of other nodes from the selected node[3].
- Location is the distance between the base station and the node. The closer the distance, the higher probability it becomes a cluster-head.
- Probability is the neural network output value between 0 and 1 for selecting cluster-heads.

To train the network, we get 50 samples from Ref. [3] and use Eq. (5) to get the weights of the winning neurons iteratively. The scheme of network learning is shown in Fig. 3.

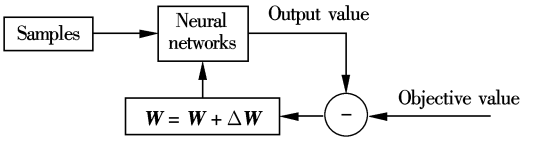

Fig. 3 Scheme of network

The weight of the winning neuron is updated according to a simple learning rule[7]

$$\boldsymbol{W}_i^{(1)}(k+1) = \frac{1}{M_i(k)} \sum_{\boldsymbol{X}_m \in \Omega_i(k)} \boldsymbol{X}_m \tag{8}$$

where $M_i(k)$ is the number of $\boldsymbol{X}_m$ included in $\Omega_i(k)$, $\Omega_i(k)$ is the set of all $\boldsymbol{X}_m$ satisfying

$$\| \boldsymbol{X}_m - \boldsymbol{W}_i^{(1)}(k) \| < \| \boldsymbol{X}_m - \boldsymbol{W}_j^{(1)}(k) \| \qquad \forall j \neq i \tag{9}$$

After the network is trained, it can be used to decide cluster-heads. We can also use the trained weight vector $\boldsymbol{W}$ to carry out network off-line learning.

Once cluster heads are elected, the base station broadcasts a message containing the list of cluster-heads' IDs to all the nodes. After that, each cluster-head announces its new status to all its neighbors. If a node around it receives the message, it registers itself to be a member of the cluster. After identifying all the members, the cluster-head node sets up a TDMA schedule and announces it to its all members. The TDMA schedule ensures that there is no collision between members and allows the radio components of member nodes to sleep in turn. When cluster formation is completed, data can be transmitted.

4 Simulation Results

For simulation experiment, the reference network consists of 115 nodes randomly distributed over an area of 1 000 m × 1 000 m. Simulation parameters are listed in Tab. 1. Each data point shown is the average of ten experiments.

Tab. 1 Simulation parameters

Type	Parameter	Value
Network	Network grid	From (0, 0) to (1000, 1000)
	Base station	At (50, 175)
Application	Data packet size/byte	100
	Broadcast packet size/byte	25
	Packet header size/byte	25
	Round/frame	5

In the first phase of the simulation nodes are assigned random energy levels between 0 and 100. The base station counts the number of neighbors for each node using a radius of 30 m. Variable number belongs to [0, 10]. And variable centrality is $\sum d^2(i)$ ($i = 0, 1, \ldots, 10$), and the maximum value of $d^2(i) = 30^2$, but $d(0) = 0$. So variable centrality is between [0, 9 000]. Variable location belongs to $[0, 1\,000\sqrt{2}]$, and the output value is between 0 and 1. In order to easily express the relationship among four variables and output, the variable centrality value belonging to [0, 9 000] is mapped to [0, 100]. Fig. 4 shows the system error as a function of training time using the RBF, where the system error is the subtraction between output and the true value. It indicates that when the training epoch's number is about 170, the system error reaches the steady value 0.003 2. Therefore, from this figure we can obtain the result that RBF network has fast training speed and good performance.

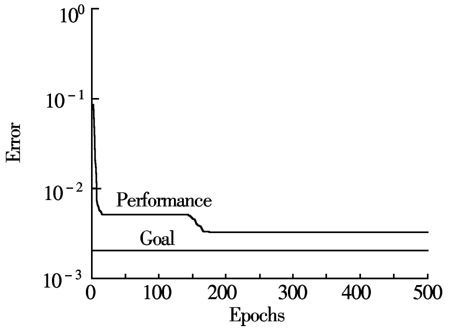

Fig. 4 Relation between error and training epochs using RBF

In order to assess our approach, we compare it with LEACH on load balance ability and network lifetime. The simulation conditions are the same as above. Standard variation of the number of nodes of each cluster of RBF and LEACH respectively is simulated by cluster radius varying from 50 to 500 m. Fig. 5 shows that the RBF standard variation is lower than that of LEACH and hence can offer better load balancing.

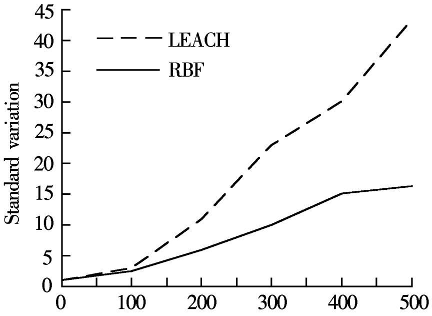

Fig. 5 Standard variation of the number of nodes of each cluster

In the following we compare network lifetime of RBF and LEACH. We assume that a node is dead when it has consumed 99% of initial energy, and that network lifetime is the number of rounds until the last node is dead. In the LEACH protocol, we obtain

$$P_i(t) = \min\left\{\frac{E_i(t)}{E_{\text{total}}(t)}k, 1\right\} \tag{10}$$

and

$$E_{\text{total}}(t) = \sum_{i=1}^{N} E_i(t) \tag{11}$$

where $E_i(t)$ is the current energy of node i, $P_i(t)$ is the probability of node i chosen to be a cluster head, k is the number of cluster heads. According to Ref. [4], here $k = 13$. We assume that the number of network nodes varies between 100 and 500. Fig. 6 shows that lifetime of network using the RBF is about 40% longer than that using LEACH. This probably results from two reasons. One is that in LEACH each node broadcasts its current energy in each round to all other nodes in the network, thus consuming much energy, while in the RBF, much smaller number cluster-heads perform this task. Secondly, the total computation load using LEACH is much heavier as nodes rather than the base station is doing the calculation.

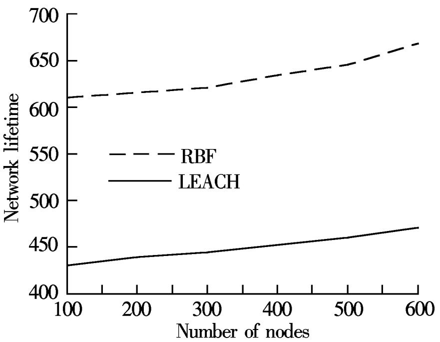

Fig. 6 Relation between network lifetime and number of nodes

5 Conclusion

In this paper, we present a scheme of cluster-head election using the RBF in WSNs. According to energy, number, centrality, location information of each node acquired from WSNs, the RBF network is used to select cluster-heads and, therefore, reduce data flowing in the network. Thus lifetime of WSNs is extended. Experimental results show that this method can select the cluster-heads quickly and significantly increase the lifetime of the sensor network.

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无线传感器网络中基于径向基函数的簇首选择

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摘要:采用一种神经网络算法——径向基函数来选择无线传感器网络的节点簇首,它具有并行处理能力、分布式存储以及快速学习等优点. 通过分析得出与节点作为簇首相关的 4 个因素:节点的剩余能量,周围分布的节点的数目,中心度和距离基站的位置. 把这 4 个因素作为神经网络的输入变量,输出变量就是该节点作为簇首的适应度值. 根据网络规模的大小,基站选出一组作为簇首的节点,然后广播作为簇首的节点号的消息. 如果一个节点被选为簇首,就向周围广播自己的身份并成立一个新簇,周围的非簇首节点要求加入该簇并成为它的成员. 每簇中由簇首负责管理它的成员并执行数据融合等功能. 实验结果表明,与其他算法相比, 该算法能显著地延长传感器网络的生命.

关键词:传感器网络;径向基函数;簇首选择

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