A Cluster Heads Selection Scheme based on CC Neural Network in WSN

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Abstract
Cascade-Correlation (CC) is a new architecture and supervised learning algorithm for artificial neural networks; it allows one to gradually build network architecture without the need to redefine the number of neurons to be used in a feed forward. It is applied to the selection of cluster heads (CHs) in wireless sensor networks (WSN), the four factors related to a node becoming a cluster head are drawn by the analysis, which are distance, remaining energy, location and vulnerability index, the factors are as input variables of neural networks and the output variable is suitability which is the degree of a node of becoming a cluster head. Compared with LEACH, the simulation shows the proposed algorithm cannot only significantly increase the lifetime of the sensor network, but efficiently decrease energy consumption of nodes.
Key words: WIRELESS SENSOR NETWORKS, CASCADE-CORRELATION NEURAL NETWORK

Introduction

Wireless sensor networks have an important practical value, they have been introduced to use in the military surveillance, environmental monitoring, industrial control, intelligent instrumentation and urban transport, etc, which have become a hot research area in recent years. Due to the limitation of energy, computing power, storage capacity and communication capacity, WSN must strive to extend the working lifetime and decrease energy consumption of nodes [1]. So many routing protocols have been devised in view of the above issues, one of these is network clustering, in which network is partitioned into small clusters and each cluster is monitored and controlled by a node, called cluster head (CH). These CHs can communicate directly with the base station (BS), other nodes send the data, sensed from the environment to these CHs, CHs first aggregates the data from the multiple sensor nodes, and then finally send it directly to the BS. Based on the analysis mentioned above, several algorithms and protocols that lead to optimal connectivity topologies for energy conservation have been proposed [2,3,4], the representative solution is LEACH [5, 6] which is a localized clustering method based on the probability model. But most of them do not simultaneously provide long lifetime system save energy consumed. All sensor nodes evenly elect itself as a CH based on the probability model to distribute the energy consumption, however, in some cases, in-efficient CHs can be elected. Because LEACH is only depend on probability model, some CHs may be very close each other and can be located in the edge of the WSN. These in-efficient cluster heads could not maximize the energy efficiency. Therefore we need more energy-efficient solution to select CHs.

In this paper, we propose an energy-efficient data aggregation algorithm based on Cascade-Correlation neural network, Cascade-Correlation is a new architecture and supervised learning algorithm for artificial neural networks. This algorithm not only automatically constructs a network but also trains the weights. With this, the number of hidden layers is not assigned in advance, but is adaptively determined during the process of learning. So the WSN system model based on the CC neural network can be rapidly established and CHs can be selected by it. Consequently, the lifetime of WSN is increased and the energy is well saved.

Cascade-correlation Neural Network

CC [7] is a new architecture and supervised learning algorithm for artificial neural networks. It begins with a minimal network, then automatically trains and adds new hidden units one by one, creating a multi-layer structure. Once a new hidden unit has been added to the network, its input-side weights are frozen. This unit then becomes a permanent feature-detector in the network, available for producing outputs or for creating other, more complex feature detectors. The CC architecture has several advantages includes: it learns very quickly, the network determines its own size and topology, it retains the structures it has built even if the training set changes.Followed by Ilona Magdisyuk's method [8], it is noted that CC combines two key ideas: The first is the cascade architecture, in which hidden units are added to the network one at a time and do not change after they have been added. The second is the learning algorithm, which creates and installs the new hidden units. For each new hidden unit, we attempt to maximize the magnitude of the correlation between the new unit’s output and the residual error signal we are trying to eliminate. The cascade architecture begins with some inputs and one or more output units, but with no hidden units. The number of inputs and outputs is dictated by the problem and by the I/O representation the experimenter has chosen. Every input is connected to every output unit by a connection with an adjustable weight. There is also a bias input, permanently set to +1 [3]. Learning starts when the network is minimal, i.e. when there is an input layer, an output layer and no hidden layers. For learning, an algorithm is used that minimises the value of the network output error, E:

$$E = 1/2\sum_{o,p}(y_{op} - t_{op})^2 \quad (1)$$

Where y_{op} is the network output for pattern p, but t_{op} is the expected output for this pattern. On the output of the network, the above described sigmoid activation function is used. Network learning is considered to be completed when the convergence of the network is achieved, that is the value of the error stops to change or if the value of the error is sufficiently small and does not exceed earlier set maximal error value. In case if the error value does not meet the above requirements, learning should be continued. For this, a new hidden layer is added to the network. This node is called a candidate node and its output is not activated in the main network at this stage. After a new hidden layer is added, all patterns out of the training sample are then passed through this node. The aim of the candidate node weights' correction is to maximise the value of correlation between the output of the candidate node and network output error, C:

$$C = \sum_{o}\left|\sum_{p}(y_p - \bar{y})(e_{op} - \bar{e}_o)\right| \quad (2)$$

where $\bar{y}$ and $\bar{e}_o$ are the mean values of the outputs and output errors over the all patterns of the training sample.

WSN System Model based on CHS with CC Neural Network

For basic WSN system model, each sensor node sends the sensed data to its CH, then the cluster head aggregates the collected data and transmits the aggregated information to the BS. Moreover it includes the following aspects: the WSN consist of the homogeneous sensor nodes; the distance can be measured based on the wireless radio signal power; once deployed, the nodes dose not move; all sensor nodes have the same initial energy; the base station is located in the outside of the WSN. The model of WSN is illustrated in Figure 1. In our method, every CH is dynamically selected by the BS in each round based on four following factors [3,8]: (1). Distance of a node from the cluster centroid. The BS calculates the distance of each node to its cluster centroid. The lesser the distance, the higher the probability that the node will become CH. (2). Remaining energy level. Obviously, the higher the energy level, the higher the probability that the node will become CH. (3). Location is the distance between the base station and the node. The closer the distance, the higher probability it becomes a CH. (4). Vulnerability index. This factor tells us how much vulnerable a node is. If it is high, then the node will not be selected as the CH [9].

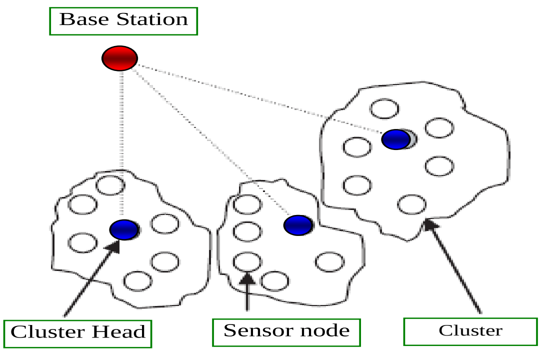

Figure 1. Model of WSN

During the WSN system setup phase, each node floods its location information and energy level to the BS. The BS puts the information acquired into the trained CC neural network, the CH is decided by the output value of the CC network. For the BS, it will produce better CH since the BS has the global knowledge about the WSN, moreover, the BS has sufficient power, memory and storage. We assume that the nodes have sufficient energy to send the location information during the initial setup phase. The radio model we have used is similar to the reference [6] with Eelec = 50nJ/bit as the energy dissipated by the radio to run the transmitter or receiver circuitry and εamp =100pJ/bit/m2 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 transmitter and receiver node is given by [8, 10]:

$$E_{Tx}\left(k,d\right)=E_{elec}\times k+\varepsilon_{amp}\times k\times d^{\lambda} \qquad (3)$$

$$E_{Rx}\left(k\right)=E_{elec}\times k \qquad (4)$$

Where λ is the path loss exponent and λ≥2.

In the CC neural network, the input vector x(t) = [Distance, mobility, Energy, Vulnerability] and the output vector y(t) = [Probability], where ‘Probability’ is the output value between 0 and 1 for selecting CH. We train the CC network by 100 samples [2] and obtain a fixed CC network, which can be used to decide CH in the WSN [11,12]. Once the CHs are decided, the BS broadcasts a message containing the list of CHs’ IDs to all the nodes, and than each CH 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 CH node sets up a TDMA schedule and announces it to its all members.

Experimental Results and Analysis

The reference network consists of 100 nodes randomly distributed over an area of 200×200 meters. The base station is located at 300, 50. During training the CC network, the system error as the training error of a function, where the system error is the SSE (sum-square error) between output and the true value. The number of the training epoch is about 16, the system error reaches the steady value 0.0028, and the corresponding structure of CC network is a 4-9-1, which is shown in Figure 2. Therefore, from this figure we can obtain the excellent performance that has fast convergence speed and high accuracy.

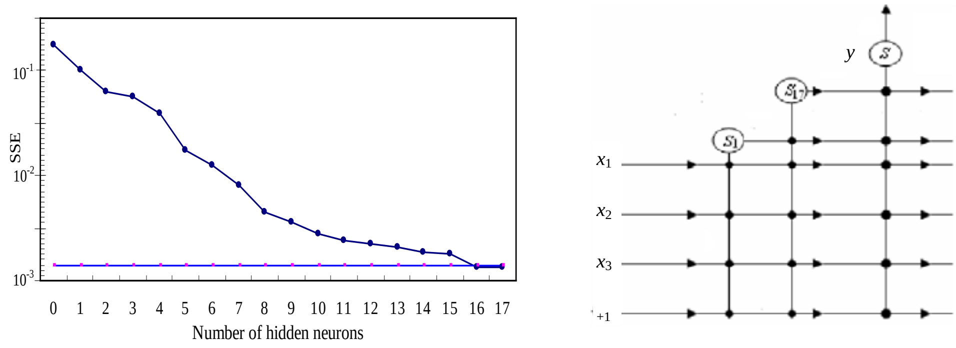

Figure 2. Training Process of CC network and network Structure

The cluster formations of the CC network and LEACH are depicted in Figure 3. In the case of LEACH, some CHs are so close each other that these clusters could not maximize the energy efficiency in general. In addition, some CHs have too many sensor nodes within the cluster because LEACH depends only on the probability model, this case makes some CHs exhaust the energy very rapidly.

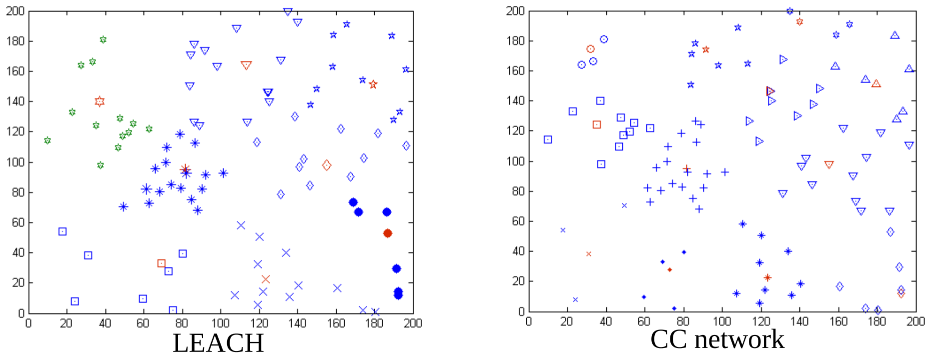

Figure 3. CHs and Cluster Formation Obtained by CC Network and LEACH

In order to assess our approach, we compare network lifetime and energy balance of CC network and LEACH in the following part [12,13,14]. Figure 4 is the lifetime of the WSN with CC network and LEACH, it can be seen that the number of round of the first dead node with CC network is about 160, but the number of LEACH is only 112. Meanwhile, the number of last dead node of CC network is about 532, is much higher than the one of the LEACH, which is only 428. Figure 5 shows the energy consumption comparison between the CC network and the LEACH at a certain round, it is clear that the sensor network optimized by the CC network can save 27.6% of energy in CHs and 27.8% in the total WSN. All the above results is compounded by the fact that the consumption energy in LEACH based on probability model is becoming unbalanced with the increasing of the round of network whereas the CHs are evenly distributed over the network in the CC network.

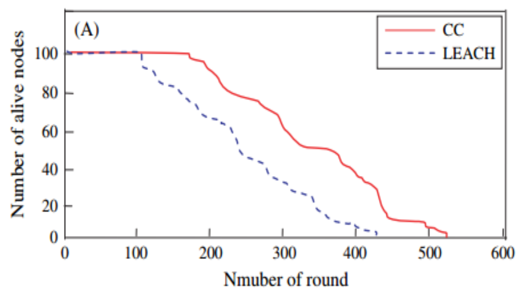

Figure 4. Network Lifetime with LEACH and CC

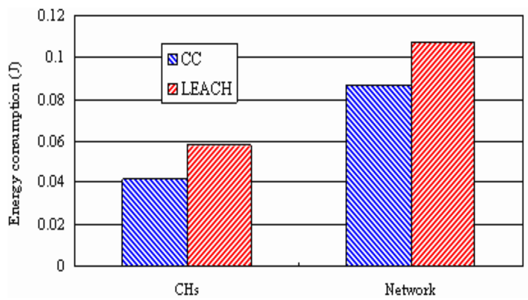

Figure 5. Energy Consumption with LEACH and CC

Figure 6 shows that the consumed energy variance of CHs as a function of rounds. The variance of consumption energy in the CC network is greatly lower than that in the LEACH, yet the CHs in the LEACH consume so much energy for taking on most of work of data transmission. Because the network is balanced in selecting proper CHs by the CC network, there is a fairly small variation in consumed energy and the energy variance curve has not obvious fluctuation in comparison with the LEACH.

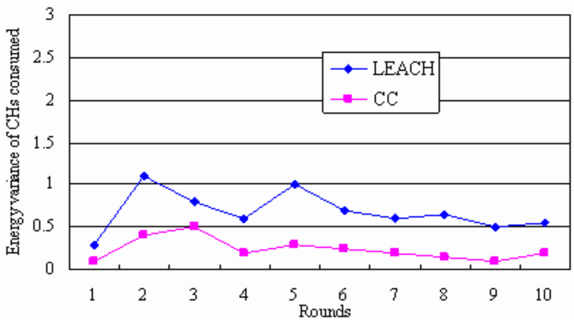

Figure 6. Relation between Consumed Energy and Rounds

Conclusions

In this paper, we present a new scheme of CHs election for wireless sensor networks using the Cascade-Correlation neural network. According to distance, remaining energy, location and vulnerability indexes of each node acquired from WSN, the CC network is used to select CHs. The experimental results show the CC network has fast convergence speed and high accuracy, therefore, the CHs are selected quickly. Compared with the LEACH, the CHs selected by the CC network can enable the WSN to reduce energy consumed and prolong the system lifetime.

Acknowledgements

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