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An Energy Consumption Control Scheme based on Radial Basis Function in Wireless Sensor Networks

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***Abstract*—Wireless sensor network node is resource constrained and difficult to replace its power. How to reduce energy consumption effectively is the practical problem. Existing literatures most designs solutions for a single application and performance evaluation protocols. Since the single node usually executes multiple applications, it is necessary to study the optimal energy consumption control scheme based on cross-application. The paper proposes a cross-application energy saving mechanism based on RBF for wireless sensor networks to control node energy consumption. Estimating cluster center using k-means clustering self-organizing algorithm based on neural network radial basis function. Then adjust and modify the weight matrix of the cluster center by Least Mean Square algorithm to realize data fusion. The simulation experiment results show that the node consumption can be significantly reduced after several rounds.**

Keywords- wireless sensor network; energy saving; cross-application; radial basis function

I. INTRODUCTION

Wireless sensor networks typically consist of millions or even tens of millions of nodes that are self-organizing nodes. The higher distribution density, the lower storage capability and the wicked deployment environment caused it's hard to replace the node power. How to reduce the energy consumption as much as possible while ensuring the regular work is the most important issue. There are many functions and applications to resolve the problem such as inhibition of network coverage area shrinking, inhibition of network hole or extending network lifetime. But this solution will make single node afford more applications within the restrained resources. The current literatures most aims at the single application to design scheme and evaluate performance. It is hard to make an optimal energy control based on cross-application.

The main energy consumption is come from data-aware, data computing and data communication. Energy consumption of data communication is the highest [1]. For the moment the researches of WSN energy control focus on the reducing the communication frequency and fusion in effect. Literature [2] proposes the duty cycling concept to manage the switching of two states between node active and node hibernation. It makes node hibernate as long as possible to save energy and prolong the network lifetime. Literature [3] studies the method of controlling energy consumption in data sampling process. Literature [4] analyses the present solutions of data aggregation and data fusion. Literature [5] presents an energy saving mechanism based on the cluster head election algorithm.

II. THE CURRENT ENERGY SAVING MECHANISM ANALYSIS

The current solution directed at one application caused some problems. At first, the discrete development will lead to that various applications have their own data package structure and nodes hibernation/active schedule. Secondly the communications between WSN nodes are mostly from adjacent nodes, that brings repeated communications. For example, we assume that WSN nodes preset energy-aware algorithms include energy-aware routing and energy-aware data integration. For the node A, its energy-aware routing function wants to know the environment energy distribution, and then it will initiate a communication to its neighbor node B to request the energy state information of node B. As well its energy-aware data integration function also wants to know the environment energy distribution, so this function also will initiate a communication to node B. That brings the repeated communications. For increasing the information efficiency of various applications, we should resolve these three questions:

1. The message reuse and decomposition;
2. The data sharing of various applications;
3. The services provision mode (design of application program interface).

III. DATA FUSION ALGORITHM BASED ON RADIAL BASIS FUNCTION

The amount of information data obtained by each sensor node in the wireless sensor network is very large and the types of data are also various. Those require the data fusion system to accurately understand and grasp the relationship between the data through continuous learning. In addition, the data collected by the sensor nodes from the outside is unreliable and incomplete, which requires the data fusion system to have better fault tolerance. The neural network can meet the above requirements well due to its own characteristics.

The artificial neural network in the data fusion technology only takes a small amount of storage space in the wireless sensor network node. It can complete the data processing very quickly. The most important function is to imitate the human mind to process the uncertain data so that data users take the right approach.

The data center is belongs to a more special device. The system's modularity allows nodes to be equipped with different types of sensors according to environmental conditions. And then it can integrate all types of data. When the node hibernates, only the acquisition and fusion module is turned on. When it detected that the node is activated, it will open the communication module. This Mechanism can significantly reduce node power consumption. The important

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point is that the algorithm designed in this paper adopted by data center greatly improves the convergence speed while the hardware requirements have declined [6-9].

In this paper, the radial basis function is chosen as the hidden layer activation function of the neural network. In order to design a RBF neural network that meets the actual requirements, the following problems need to be solved after getting enough training samples:

First, the number of hidden nodes in the neural network must be confirmed. And then the cluster center, the expansion constant, and the output weight matrix of each cluster domain are determined. The core of building a neural network is to select a sample clustering center. The most convenient way is to use all samples as a clustering center. The advantage of this method is that the computational complexity is low and it is suitable for small networks with fewer variables [10].

As shown in Figure 1, assume that there are N inputs, K hidden nodes, and M outputs in the neural network. Suppose the input vector is $I_y = (v_{i1}, v_{i2}, ..., v_{in}) \in R^N$, $W \in R^{K\times M}$ is the output weight matrix, $O=[O_1,O_2,...,O_M]$ is the network output vector set, φ_i is the activation function of the i-th hidden node.

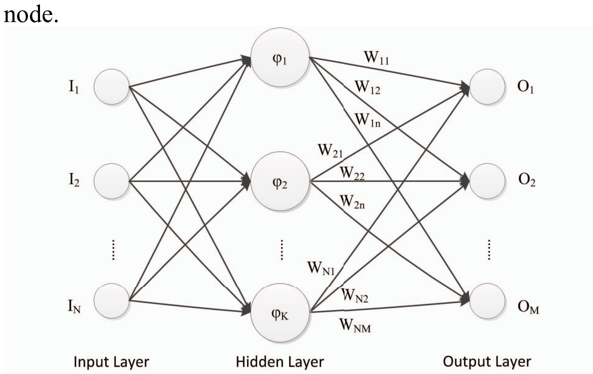

Figure 1. RBF neural network

In the above figure, the data center receives each type of data from the application layer as an input sample. The middle layer is a hidden layer, which is composed of hidden nodes. The transformation function uses the RBF function. In this paper, the radial Gaussian function is used as the radial balance attenuate non-negative function and nonlinear function of the center point [11]. The output layer uses a linear activation function.

There are many ways to select a clustering center in RBF. This paper uses a self-organizing method called k-means clustering. The algorithm has two phases: the self-organizing learning phase and the supervised learning phase. In the first phase, it will estimate the center of the cluster and then continuously adjust the weight based on the mean squared error of the expected value and the output value of the second stage.

Suppose n is the iteration times, and the cluster center of the n-th iteration is $C_1(n)$, $C_2(n)$,..., $C_K(n)$. The corresponding clustering domain is $D_1(n)$, $D_2(n)$,..., $D_K(n)$. The steps of the algorithm are as follows:

1. Randomly select K various initial clustering center. n=1.
2. Caculate the distance between all of the input samples and clustering center $\|I_y - C_x(n)\|$, $x \in [1, K]$, $y \in [1, N]$.
3. Based on the minimal distance principle to classify the input samples I_y, calculate the minimum distance between the sample and the cluster center $\min\|I_y - C_x(n)\|, x \in [1,n]$, $I_x \in d_y(k)$.
4. Recounting the new clustering center based on $C_x(n+1) = \sum_{j\in D_x(n)} j / N_x$, and N_x is the count of $D_x(n)$.
5. If $C_x(n+1) \neq C_x(n)$, goto the 2nd step. Else the clustering is finished and the cluster center is $C_x(n)$, goto the 6th step.
6. The expansion constant depends on the distance $\min_x \|C_y - C_x(n)\|$.

After determining the cluster center and the expansion constant, the weight matrix W of the cluster center to the output point can be continuously adjusted and corrected using the minimum mean square error algorithm. The steps of the algorithm are as follows:

1. Assuming that the input vector is $I_y = (v_{i1}, v_{i2}, ..., v_{in}) \in R^N$, the i-th cluster center node, and the output value of the i-th hidden node is $\varphi_i(\|I_y - C_i\|)$, the output matrix of all hidden nodes can be expressed as $H \in R^{N\times K}$

2. If the current weight matrix is $W \in R^{K\times M}$, then the output prediction matrix for all input samples is $O = HW = [H_1W_1, H_2W_2, ..., H_NW_M] \in R^{N\times M}$

3. Assuming that the output matrix of the test set is $O_{test} = [Ot_1, Ot_2, ..., Ot_N] \in R^{N\times M}$, then the mean square error MSE of the i-th output vector is calculated as follows:

$$MSE = \frac{\sum_{j\in[1,N]} (Ot_{ij} - H_jW_i)^2}{n} , \ i \in [1, M]$$

4. Solve the parameters W_i using the least squares method to minimize the MSE, and obtain the modified weight vector parameters W_i , which satisfy the smallest mean square of the difference between the predicted value and the true value.

IV. SIMULATION EXPERIMENT AND PERFORMANCE ANALYSIS

In this paper, the ZigBee module is used to build the network. The Arduino tool is used to develop the ZigBee driver and embed the MCU to form the central node. Using the MATLAB simulation tool, 500 sensor nodes are randomly placed in the 30m × 30m area to form the simulated neural network. All nodes are connected to each other, and the initial energy of each node is set to be the same. The central node continually corrects the weight matrix and threshold by the least mean square error algorithm and sends it to the terminal node. The terminal node sensor performs data fusion through the new weight matrix and threshold. Then monitors and analyzes the sampling result through MCU programming, and then compares the performance of the energy control strategy and data fusion algorithm with the traditional BP algorithm.

As shown in Figure 3, the proposed algorithm achieves energy transmission adaptation through the cross-application resource scheduling scheme on the node, which can reduce the working intensity of the node in the transmission period and perform data fusion according to the algorithm. Compared to the DSPC algorithm using periodic polling, the total energy consumption of the node of the algorithm is lower than the total energy consumption of the traditional algorithm after multiple rounds of execution.

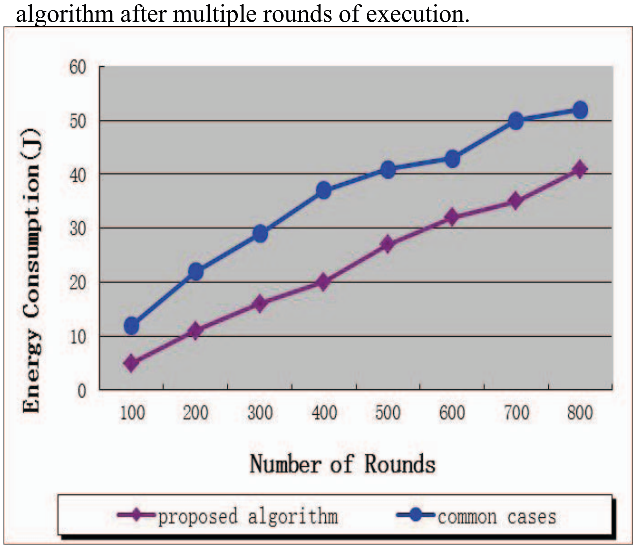

Figure 2. Total energy consumption.

Compared with ordinary nodes, the life cycle of data fusion node significantly improved. With the continuous improvement of the number of nodes, the information transmission will also consume a relatively high amount of power. Under these circumstances, the advantage of algorithm proposed in this paper is more obvious. Apply the optimization fusion algorithm to WSN's ZigBee network can achieve the purpose of long-distance and low-power information transmission.

Compared with the common nodes using the traditional BP algorithm, the life cycle of the nodes using the improved algorithm is also significantly improved. As the number of nodes continues to increase, information transmission will also consume relatively high power. In this case, the advantages of the algorithm proposed in this paper will be more obvious. Figure 4 compares the convergence speed of the proposed algorithm and the traditional BP algorithm at different number of nodes. It can be seen from the experimental results that when the CPU frequency of the single chip microcomputer is higher than 2000 Hz. The convergence speed of the algorithm is only related to the number of nodes.

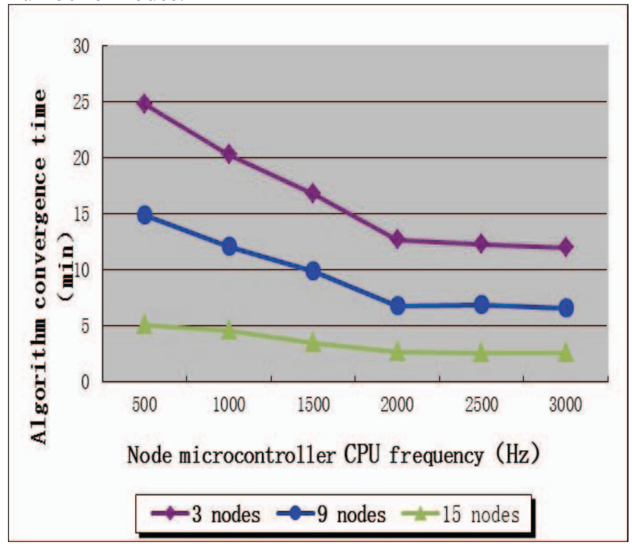

Figure 3. Algorithm convergence time

It can be seen from the above simulation results that the optimized data fusion algorithm can effectively reduce the energy consumption of the node. The optimized fusion algorithm is applied to the ZigBee network of the wireless sensor network, which can achieve the purpose of long-distance and low-power information transmission.

V. CONCLUSION AND PROSPECT ANALYSIS

The key issue in wireless sensor networks today is how to optimally work together for a variety of applications under resource-constrained conditions. In order to solve these problems in the implementation process, this paper presents a new solution.

The solution considers sharing data from multiple applications in two ways: data storage and data communication. It can improve the efficiency of data storage and reduce repeated communication.

In the solution, data center nodes are introduced for data scheduling, maintenance, and local storage to reduce the number of communications. In terms of data storage, artificial neural network data fusion algorithms are used for data fusion. The algorithm currently analyzes and fuses data information based on the original detection data. The future work is to extract the features of the data, analyze and classify the data of multiple sensor nodes and multiple applications based on the extracted feature information. Then perform data fusion of target states and features.

On the basis of analyzing the current research on wireless sensor networks, coordinating various application resources and enhancing application information sharing is a new breakthrough in controlling energy consumption. Based on the above research hotspots, this paper studies the basic solutions and key technologies of energy consumption control when nodes run multiple applications. The research results can be applied to wireless sensor networks or similar IoT structures.

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