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Distributed Optimization of Lifetime of Wireless Sensor Networks based on Mutually Connected Neural Networks

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Abstract— **The wireless sensor networks, which collect various information from a physical environment, are usually designed as an ad hoc network consisting of a huge number of tiny wireless sensor nodes whose computing power and battery capacity are limited. Because it is difficult to replace all of batteries on such a huge number of sensor nodes, maximization of the lifetime of the network has been one of the important research issues. To optimize such a network with a huge number of the sensor nodes, autonomous and decentralized computing and reconfiguration schemes are suitable. Therefore, in this paper, we propose a routing reconfiguration scheme based on an autonomous optimization dynamics of mutually connected neural networks which minimize their own energy function by autonomous and distributed computing. We show that the proposed method can optimize the routing to maximize the lifetime of the multi-hop wireless sensor network, without any centralized computing nodes.**

I. Introduction

Various technologies to realize ubiquitous computing environment have been important research topics over the last decade [1]. The target of those researches is to make everything in the physical world be smart device and react according to various kinds of information collected through the networks. The wireless ad hoc sensor networks have been studied as one of enabling technologies of such a network to connect any devices in the physical real world. One of the most important goals of the wireless ad hoc sensor networks is to realize a network of huge number of tiny sensor nodes whose computing power and battery capacity are limited. Since it is very difficult to replace the batteries for a huge number of sensor nodes, maximization of the network lifetime by efficient utilization of available energy has been one of the most important issues for the wireless ad hoc sensor network research, such as the technologies for realizing compact device, low-power-consumption communication hardware, routing protocols and so on. Short range wireless communication systems such as ZigBee and low rate UWB are examples for such a low-power consumption wireless systems suitable for wireless sensor networks.

To realize a power efficient wireless ad hoc network and maximize its lifetime, the network routing protocol should be also optimized. Since the transmission range of each sensor node is limited in such low-power-consumption transmission technologies, the architecture of the wireless sensor networks is usually multi hop ad hoc networks as shown in Fig. 1. In such multi-hop networks, when the residual battery of a wireless node on the route from the data source node to the destination node is run down, communications between this pair of source and destination becomes unavailable if there are no other wireless nodes which can relay the data between them. Therefore, it is important to optimize the routing to prolong the lifetime of the wireless sensor networks by avoiding running down of all sensor nodes and balancing energy consumption among the sensor nodes.

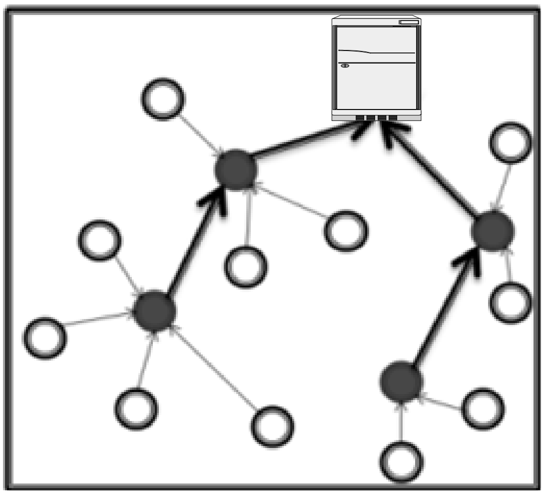

Figure 1. Wireless ad hoc sensor networks.

Various routing algorithms to maximize the lifetime of wireless sensor networks have been proposed. It is well-known that the algorithms, which dividing the sensor nodes to several clusters and aggregate information at the cluster head node, are power efficient [2]. Even in such cluster-based routing algorithms, optimization of multi hop routing between the cluster heads is still necessary [3].

To optimize the energy efficiency and maximize the lifetime of the wireless sensor networks, distributed and autonomous methods should be suitable, because the wireless sensor networks always include huge number of sensor nodes. As one of distributed and autonomous optimization methods, mutually connected neural networks [4] have been applied to various combinatorial optimization methods. In Ref. [5,6], we have already shown that autonomous and decentralized optimization by the mutually connected neural network dynamics is useful for decentralized optimum decision making for radio resource usage in heterogeneous wireless networks including various radio access networks and various operator networks, in which centralized decision making is not applicable.

In this paper, we propose a distributed and autonomous routing optimization method for wireless ad hoc sensor networks to maximize their lifetime using the optimization dynamics of mutually connected neural network. We show how to design the proposed algorithm based on the neural network and then we analyze its performances.

II. SENSOR NETWORK ROUTING BASED ON DYNAMICS OF MUTUALLY CONNECTED NEURAL NETWORKS

A. Mutually Connected Neural Networks

It is well-known that the mutually connected neural network, whose update equation is given by very simple equation based on the weighted summation and the threshold as the following equation,

$$x_{ik}(t+1) = \begin{cases} 1 & \text{if } \sum_{j=1}^{N}\sum_{l=1}^{N} W_{ikjl}x_{jl}(t) - \theta_{ik} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

converges to the state of the minimum of the following energy function since each neuron update decreases this energy function autonomously,

$$E(t) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} W_{ikjl}x_{ik}(t)x_{jl}(t) + \sum_{i=1}^{N}\sum_{k=1}^{N}\theta_{ik}x_{ik}(t), \quad (2)$$

where $x_{ik}(t)$ is the output of the *ik* th neuron at time *t*, W_{ikjl} is the connection weight between the *ik* th and the *jl* th neurons, θ_{ik} is the threshold of the *ik* th neuron, respectively [4].

This convergence dynamics of the neural network corresponding to the minimum of the energy function has been applied to various combinatorial optimization problems, such as Traveling Salesman Problems, Quadratic Assignment Problems and so on. To improve the performance of this approach, various stochastic search [7,8] and chaotic search [9,10] have been proposed, and the effectiveness of chaotic dynamics for optimization problems has been shown by various researches.

In this paper, we apply such a mutually connected neural network as an optimization tool to distributed and autonomous routing reconfiguration of the wireless ad hoc sensor networks.

B. Mapping the State of Multi-Hop Sensor Network onto the State of the Neural Network

In order to apply the dynamics of the mutually connected neural networks to an optimization problem, first we have to define each state of the target optimization problem by the states of firing patterns of the neural network. In this paper, we map the state of the solution of the multi-hop routing of the wireless sensor network to the state of neural network by a relation shown in Fig. 2.

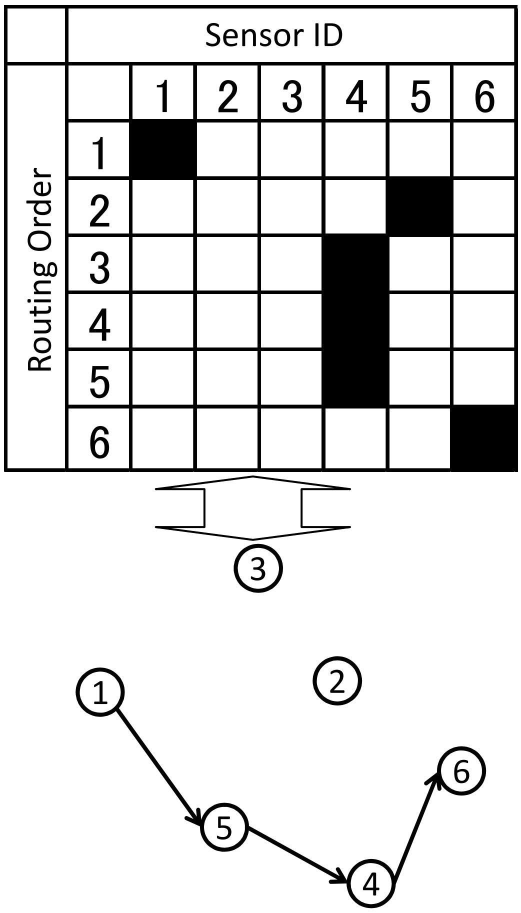

Figure 2. Relation between the state of the neural network and routing of the wireless sensor networks.

As shown in Fig. 2, firing of the (*i, j*) th neuron is corresponded to that the sensor node *i* comes to the *j* th hop of the multi-hop routing. In the example shown in Fig. 2 which consists of six sensor nodes, sensing data is sent from the sensor node 1 to the sensor node 6. The firing of three neurons corresponding to the third, fourth and fifth hops for the sensor node 4 means that the node between the node 5 and the node 6 is only the node 4. Since the number of hops in the multi-hop sensor network varies depending on the situation, such as the distance to the destination node, the current distances between the sensor nodes and the residual power of each sensor, the algorithm should be flexible and adaptive to the optimum number of hops.

To run this neural network to optimize the sensor network routing, first the states of the neurons corresponding the order 1 for the source node s and the last order for the destination node d are preset 1. The states of other neurons corresponding to these two nodes are set 0, as follows,

$$x_{s,j}(t) = \begin{cases} 1 & \text{for } j = 1 \\ 0 & \text{for } j \neq 1 \end{cases}, \tag{3}$$

$$x_{d,j}(t) = \begin{cases} 1 & \text{for } j = N \\ 0 & \text{for } j \neq N \end{cases}, \tag{4}$$

where, N is the number of sensor nodes in the sensor network. The neurons corresponding to these two neurons are kept constant and not updated. The initial states of the neurons corresponding to other sensor nodes are decided randomly and updated by Eq. (1). In the example of Fig. 2, the states of the neurons $x_{1,1}(t)$ for the source node 1 and $x_{6,6}(t)$ for the destination node 6 are kept 1, and the states for other neurons corresponding to these two sensor node are kept 0. The neurons corresponding to other sensor nodes are updated by Eq. (1) autonomously on each sensor node without centralized computation, and the state of the neural network converges to a state corresponding to the optimal routing configuration of the multi-hop sensor network.

C. Energy Function and Connection Weights

The target of optimization of the wireless sensor networks is to maximize the lifetime of the network. In order to maximize the lifetime, we introduce the following three types of objective energy functions, based on the mapping of neurons described in previous subsection.

The first objective energy function is maximization of the total of the residual energy of sensors which are selected in the multi-hop network configuration. By using the state of the neurons, this energy function can be defined by the following equation,

$$E_1 = \sum_{i=1}^{N}\sum_{k=1}^{N} \frac{1}{\left(\dfrac{R_i}{\max\limits_m R_m}\right)} x_{ik}(t), \tag{5}$$

where R_i is the residual energy of the i th sensor node. The second energy function is minimization of total required energy in the selected routing, which can be defined as follows,

$$E_2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} \frac{e_{ij}}{\left(\dfrac{R_i}{\max\limits_m R_m}\right)} x_{ik}(t)x_{jk+1}(t) + \frac{e_{ij}}{\left(\dfrac{R_j}{\max\limits_m R_m}\right)} x_{ik}(t)x_{jk-1}(t), \tag{6}$$

where e_{ij} is energy required for exchanging data between the i th and the j th sensor node. The third energy function is the constraint term for controlling the number of neurons corresponding to each routing order to be 1. It can be defined by the following equation,

$$E_3 = \sum_{k=1}^{N}\{\sum_{i=1}^{N} x_{ik}(t) - 1\}^2 . \tag{7}$$

From these three energy functions, the total energy function to be minimized is defined as follows,

$$E_{\text{TOTAL}} = AE_1 + BE_2 + CE_3, \tag{8}$$

where, A, B and C are the weights of each energy function, respectively.

By comparing the objective function in Eq. (8) and the energy function of neural network in Eq. (2), we can obtain the connection weight and threshold as follows,

$$W_{ikjl} = -2B\left\{\frac{e_{ij}}{\left(\dfrac{R_i}{\max\limits_m R_m}\right)}\delta_{l,k+1} + \frac{e_{ij}}{\left(\dfrac{R_j}{\max\limits_m R_m}\right)}\delta_{l,k-1}\right\} - 2C\delta_{kl}(1-\delta_{ij}), \tag{7}$$

$$\theta_{ik} = A\frac{1}{\left(\dfrac{R_i}{\max\limits_m R_m}\right)} - C, \tag{8}$$

where δ_{ij} is the Kronecker delta.

III. Neural Network Based Reconfiguration Method and its Performance

In the proposed method, computations for updating neurons are distributed to each sensor node. Optimum routing is autonomously solved by distributed update of neurons on each sensor, which decides the next hop node by firing patters on neurons.

When we implement distributed computation in such a way, the total amount of traffic which has to be exchanged for updating all neurons can be estimated as shown in Fig. 3. In Fig. 3, amount of signaling data traffic required for sending data occurred in each session are compared with an ad hoc network protocol which maximize capacity (CMAX) [11] as one of ad hoc network protocol, and OML (Online Heuristic for Maximum Lifetime Routing)[3]. In this analysis, it is assumed that each sensor may move and distances between sensor nodes have to be updated in each reconfiguration of the multi-hop networks. Under such an assumption, from Fig. 3, it is clear that the proposed method based on the mutually connected neural network reduces the amount of data in larger sensor networks.

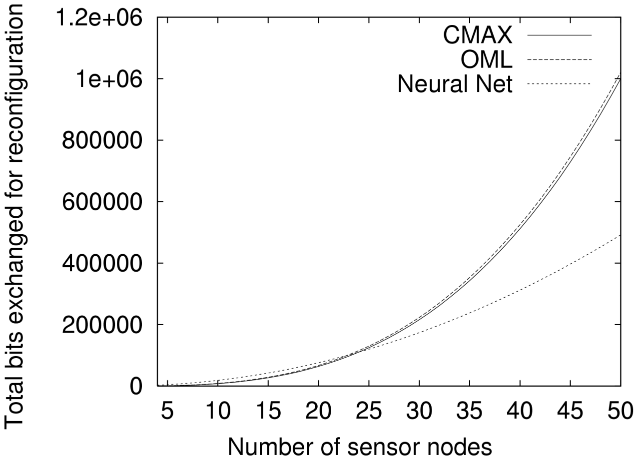

Figure 3. Amont of transmitted data required to run each algorithm to optimize the wireless multi-hop sensor networks.

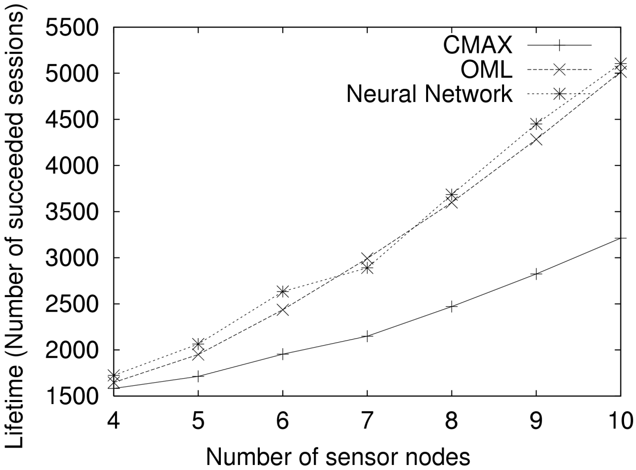

Figure 4. Lifetime of the wireless sensor networks configured by the proposed method using neural network dynamics, OML and CMAX.

In Fig. 4, we show the simulation results of the lifetime of the sensor networks. The proposed method based on the neural network performs better than the CMAX. Although the performance is almost the same as OML, the proposed method requires fewer amount of signaling packets which should be exchanged as shown in Fig. 3.

Since the OML requires centralized computing, the amount of traffic increases huge as shown in Fig. 3. Furthermore, such centralized method leads to longer delay to start data transmission, because calculation of optimum routing configuration requires sending of the state of each sensor node to the centralized computation node and the calculated optimum configuration have to be informed to each sensor node.

On the other hand, the proposed method does not require gathering information to such a centralized node. Amount of signaling traffic consequently becomes very small as shown in Fig. 3, and transmission delay becomes very small. The wireless sensor network can be autonomously converges to an optimal state based on the firing patters of neurons on each sensor node by distributed computation.

IV. CONCLUSION

In this paper, we have proposed an autonomous and distributed routing optimization algorithm for maximizing the lifetime of the wireless sensor networks. Since the proposed methods does not require centralized computing, it is power efficient than the conventional methods. Furthermore, the proposed method does not require gathering of real-time information to a centralized computing node, computational time and transmission delay can be also reduced.

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