2017 International Symposium on Nonlinear Theory and Its Applications,
NOLTA2017, Cancun, Mexico, December 4-7, 2017

A Flooding Scheme in Wireless Sensor Networks Using a Discrete-Valued Neural Network

Hidehiro Nakano† and Arata Miyauchi†

†Faculty of Knowledge Engineering, Tokyo City University
1–28–1, Tamazutsumi, Setagaya-ku, Tokyo 158-8557, Japan
Email: hnakano@tcu.ac.jp, miyauchi@ic.cs.tcu.ac.jp

Abstract—In wireless sensor networks, flooding is used in diffusing advertising messages, control messages, and so on. If forwarding nodes which perform the flooding are properly selected from all the wireless sensor nodes, the messages can be efficiently diffused. Also, if plural forwarding node sets are obtained and these sets are switched periodically, the load balancing of each wireless sensor node can be realized. This paper proposes a method using a discrete-valued neural network for solving this problem. Through numerical simulations, we confirm the effectiveness of the proposed method.

1. Introduction

In Wireless Sensor Networks (WSNs), the status of large-scale observation area can be measured remotely, by constructing impromptu networks and using multi-hop wireless communication between each wireless sensor node [1, 2]. The wireless sensor nodes collect the status information around them, and transmit it to a sink node.

In WSNs, flooding is used in diffusing advertising messages, control messages, and so on. The flooding is realized by broadcasting the messages from each wireless sensor node to its neighbor wireless sensor nodes. A wireless sensor node receiving the messages transmits them also by performing the flooding. By repeating in this manner, the messages are diffused to all the wireless sensor nodes. However, it is not needed that all the wireless sensor nodes perform the flooding. By properly selecting Forwarding Nodes (FNs) which perform the flooding, the massages can be efficiently diffused to all the wireless sensor nodes. Then, the energy consumption of the wireless sensor nodes without performing the flooding can be saved.

In our previous works, a flooding scheme using a neural network has been proposed [3]. In this scheme, each wireless sensor node is represented by a neuron element, each established 1-hop link between the neighbor wireless sensor nodes is represented by a neuron coupling. Then, the WSN is represented by a neural network. As each neuron decides a firing state, the corresponding node becomes an FN. Each neuron refers to the history of the internal states of the neuron itself and of the firing state of its neighbor neurons. This scheme can also obtain plural different FN sets by repeating the update of the internal states of the neurons. By switching the FN sets periodically, the load balancing of each wireless sensor node can be realized.

If the calculation of each neuron can be implemented on each wireless sensor node, autonomous-distributed control can be realized. However, in the conventional scheme, the internal states of each neuron are represented by real numbers. It is hard to implement on simple hardware, because the circuit amount of memory elements and calculation units becomes large.

This paper proposes a flooding scheme using a discrete-valued neural network. In this scheme, each neuron has integer-valued internal states, and calculates them by integer units. Therefore, the hardware costs for the implementation of the neurons can be saved. For a WSN model as a test environment, the simulation experiments are performed. We evaluate the performance about the number of selected FNs and the load balancing of each wireless sensor node. Also, we investigate a proper bit-length for the representation of each neuron. The proposed scheme can be easily implemented on simple hardware, keeping the performance compared with the conventional scheme.

2. A Selection Problem for Forwarding Node Sets

In Wireless Sensor Networks (WSNs), flooding is used in diffusing advertising messages, control messages, and so on. As a simple flooding scheme, each wireless sensor node receiving messages broadcasts them to its neighbor wireless sensor nodes at once. By repeating in this manner, the messages are diffused to all the wireless sensor nodes. However, it is not needed that all the wireless nodes perform the flooding. By properly selecting Forwarding Nodes (FNs) which perform the flooding, the massages can be efficiently diffused. We refer to it as a selection problem for FNs. In addition, specific FNs continue to perform the flooding, only their energy consumption becomes large. Therefore, plural FN sets are obtained and they are switched periodically. Then, the load balancing of each wireless sensor node can be realized. We refer to it as a selection problem for plural FN sets. For solving these problems, we have proposed a flooding scheme using a neural network [3]. However, in the conventional scheme, the internal states of each neuron are represented by real numbers. It is hard to implement on simple hardware.

3. A Flooding Scheme Using a Discrete-Valued Neural Networks

In this section, a flooding scheme using a discrete-valued neural network is proposed. Each wireless sensor node is represented by a neuron element. Each established 1-hop link between the neighbor wireless sensor nodes is represented by a neuron coupling. Let the bit-length of each internal state value be N. The dynamics of the i-th neuron is described by

$$x_i(t+1) = S(y_i(t+1)) \quad (1)$$

$$S(z) = \begin{cases} 1, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}$$

$$y_i(t+1) = L(\xi_i(t+1) - \eta_i(t+1) - \zeta_i(t+1)) \quad (2)$$

$$\xi_i(t+1) = L\left(\sum_{j \in D_i} 1\right) \quad (3)$$

$$\eta_i(t+1) = L\left(\left(\frac{1}{2} + \frac{1}{2^2}\right)\eta_i(t) + \sum_{j \in D_i} x_j(t)\right) \quad (4)$$

$$\zeta_i(t+1) = L\left(\left(\frac{1}{2} + \frac{1}{2^2}\right)\zeta_i(t) + 2^{N-2}x_i(t)\right) \quad (5)$$

$$L_s(z) = \begin{cases} 2^{N-1} - 1, & \text{if } 2^{N-1} - 1 < z \\ z, & \text{if } -2^{N-1} \leq z \leq 2^{N-1} - 1 \\ -2^{N-1}, & \text{if } z < -2^{N-1} \end{cases}$$

where x_i is a binary-valued output, and y_i, ξ_i, η_i and ζ_i are N bit integer-valued internal states. Note that ξ_i, η_i and ζ_i always take positive values, they can be memorized by $(N-1)$ bit in fact. D_i is an index set of the neighbor neurons (wireless sensor nodes) of the i-th neuron. $S(\cdot)$ is an activation function, and $L(\cdot)$ is a saturation function. The parameter values are fixed based on power of two, which can be calculate by simple addition and shift operations. The summation operations in Eqs.(3) and (4) are realized only by counting the neighbor nodes and the neighbor FNs, respectively. If the i-th neuron output $x_i = 1$, the neuron is said to be fire.

By regarding a firing neuron as an FN, the autonomous-distributed decision of FN sets can be realized. In this paper, in order to decide FN sets so that all the wireless sensor nodes can certainly receive messages, the following decision algorithm is used.

1. Let all the sensor nodes be undecided nodes UNs.
2. Let a sink node be a forwarding node FN.
3. Calculate distance r_{kl} between each UN_k and each FN_l.
4. Find UNs satisfying $r_{kl} < R_T$.
5. Change the found UNs into receiving nodes RNs.
6. If all the UNs become RNs or FNs, finish this algorithm.
7. Calculate distance r_{kl} between each RN_k and each UN_l.
8. Find RNs with neighbor UNs satisfying $R_E < r_{kl} < R_T$.
9. Select an RN whose y_k is the largest in the found RNs.

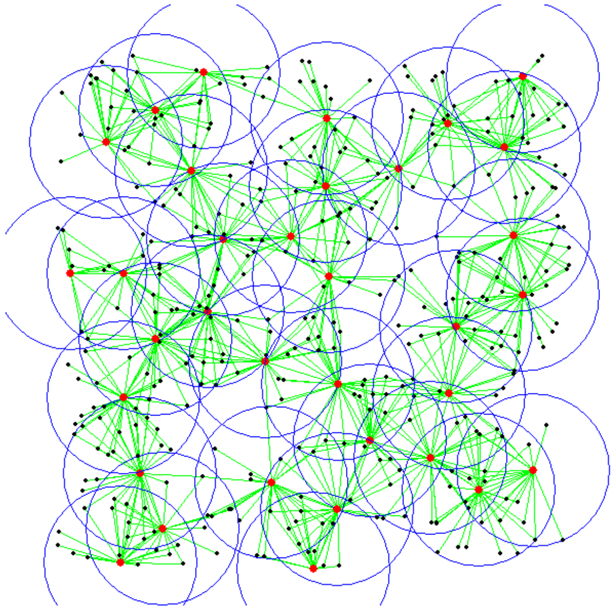


Figure 1: A solution obtained by the greedy scheme（Number of FNs: 33）

Table 1: Simulation parameters for a WSN model.

Area size	(0,0) ~ (1000,1000)
Location of a sink node	(500,0)
Number of wireless sensor nodes	400
Transmission range R_T	150
Exception range R_E	100

10. Change the selected RN be a forwarding node FN.
11. Go to 3.

In the above algorithm, k and l are the indexes of the wireless sensor nodes. R_T and R_E are the parameters of transmission range and exception range, respectively.

Note that in the conventional scheme, each internal state is represented by real numbers without using the saturation function $L(\cdot)$, and the sigmoid function is used as the activation function $S(\cdot)$ [3]. This is a kind of the chaotic neural network models for solving combinatorial optimization problems [4, 5].

Also, note that a greedy scheme without using the neuron dynamics can be constructed if the step 9 in the above algorithm is replaced with the following.

9'. Select an RN which has the most UNs in the found RNs.

It will be used as the comparative method.

4. Simulation Experiments

In this section, simulation experiments are performed. Table 1 shows the simulation parameters for a WSN model.

Table 2: Simulation parameters for each neuron in the conventional scheme

C_ξ	0.01
C_η	0.01
k_η	0.75
k_ζ	0.75
α	1

The following three methods are compared.

1. Proposed scheme with a discrete-valued neural network
2. Conventional scheme with a real-valued neural network
3. Greedy scheme without the neuron dynamics.

For the proposed scheme, the bit-length N is changed from 5 to 7. Table 2 shows the simulation parameters for each neuron in the conventional scheme.

Fig.1 shows the FN set obtained by the greedy scheme. This is the basic result in order to evaluate the proposed scheme. Fig.2 shows the FN sets obtained by the proposed scheme for $N = 6$. It can be seen that different FN sets are obtained at each trial.

Next, the number of selected FNs for 50 trials (from $t = 1$ to $t = 50$) is evaluated. Fig.3 shows the comparison results. The vertical axis represents the number of FNs, and the horizontal axis represents the sorted trials. The number of FNs by the greedy scheme is the least in all the schemes. However, the greedy scheme without using the neuron dynamics can always obtain only a specific FN set. The proposed and conventional schemes show almost the same results.

Next, we evaluate the number of times such that each wireless sensor node is selected as FN. In this experiment, the load balancing of each wireless sensor node is evaluated. Fig.4 show the results. The vertical axis represents the number of times, and the horizontal axis represents the sorted wireless sensor node indexes. The greedy scheme without the neuron dynamics can always obtain only a specific FN set. The proposed and conventional schemes can obtain plural different FN sets. In the actual use, as plural FN sets are switched periodically, the load balancing of each wireless sensor node can be realized.

In the proposed scheme for $N = 5$, the calculation accuracy decreases, and the load balancing becomes insufficient. On the other hand, in the proposed scheme for $N = 6$ and $N = 7$, almost the same results as the conventional scheme are obtained. In the other experiments, we have confirmed that this trend was not changed for $N \geq 8$. The proposed scheme can reduce the bit-length with keeping the performance. From the results, the proper bit-length for the WSN is clarified. The proposed scheme can be implemented on simple hardware. Also, it will be possible to realize autonomous-distributed control by implementing the neurons in the proposed scheme on each wireless sensor node.

5. Conclusions

In this paper, we have proposed a discrete-valued neural network for solving selection problems for forwarding nodes in wireless sensor networks. The proposed scheme can reduce the bit-length for the calculation of each neuron, and the proper bit-length with keeping performance has been clarified in the simulation experiments. The proposed scheme can be implemented on simple hardware, compared with the conventional scheme by using a real-valued neural network.

Future problems include (1) the consideration for the forwarding power adjustment scheme [6, 7], (2) the circuit implementation of the proposed scheme, (3) the realization of the autonomous-distributed control, and (4) the comparison with the other algorithms.

References

[1] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," Computer Networks Journal (Elsevier), vol. 38, no. 4, pp. 393-422, 2002.

[2] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," Proc. of the Hawaii International Conference on System Sciences (HICSS), pp. 3005-3014, 2000.

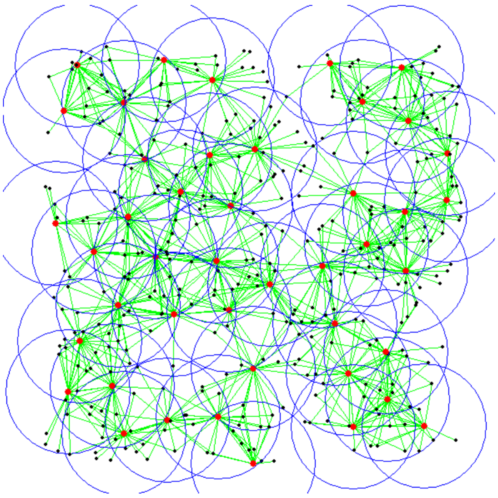
[3] T. Sasaki, H. Nakano, A. Utani, A. Miyauchi and H. Yamamoto, "An Adaptive Selection Scheme of Forwarding Nodes in Wireless Sensor Networks Using a Chaotic Neural Network, " ICIC Express Letters, vol. 4, no. 5(A), pp. 1649-1655, 2010.

[4] M. Hasegawa, T. Ikeguchi, K. Aihara, "Solving Large Scale Traveling Salesman Problems by Chaotic Neurodynamics," Neural Networks, vol. 15, no. 2, pp. 111-123, 2002.

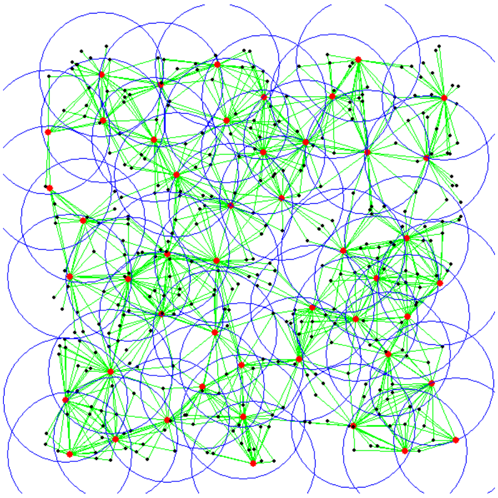
[5] M. Hasegawa, T. Ikeguchi, K. Aihara, K. Itoh, "A Novel Chaotic Search for Quadratic Assignment Problems," European Journal of Operational Research, vol. 139, no. 3, pp. 543-556, 2002.

[6] H. Lee, H. Nakano, and A. Miyauchi, "A Tabu Artificial Bee Colony Algorithm for Effective Forwarding Power Adjustment in Wireless Sensor Networks," Proc. NOLTA, pp. 227-230, 2012.

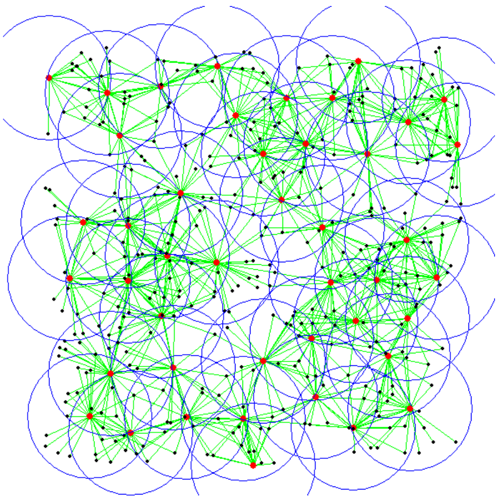
[7] R. Sato, H. Nakano, and A. Miyauchi, "A Power Optimization Method in Large-Scale Wireless Sensor Networks Using a Two-Stage Meta-Heuristic Algorithm," Proc. NOLTA, pp. 302-305, 2013.



(a) t = 1 （Number of FNs: 43）

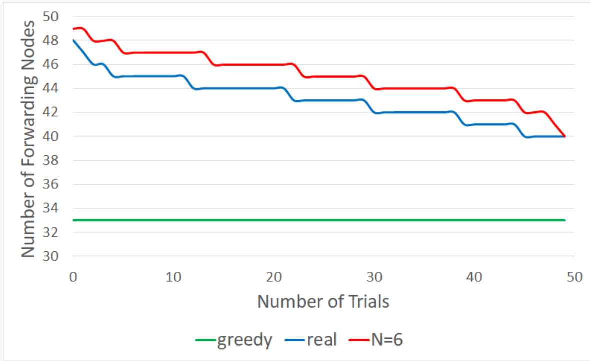


(b) t = 2 （Number of FNs: 47）

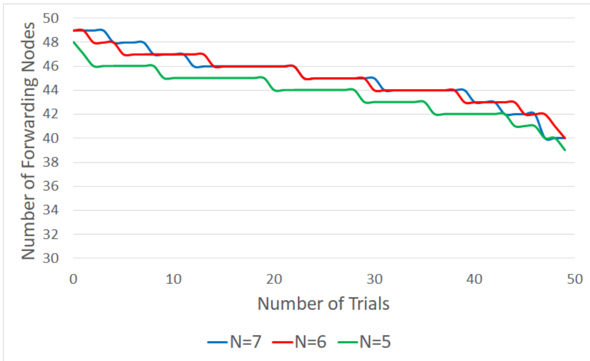


(c) t = 3 （Number of FNs: 43）

Figure 2: Solutions obtained by the proposed scheme (N = 6)

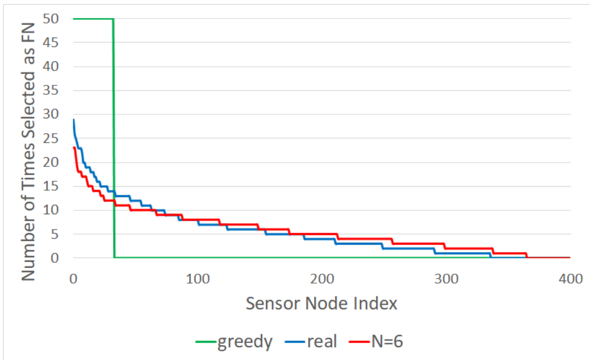


(a) Comparison for each scheme

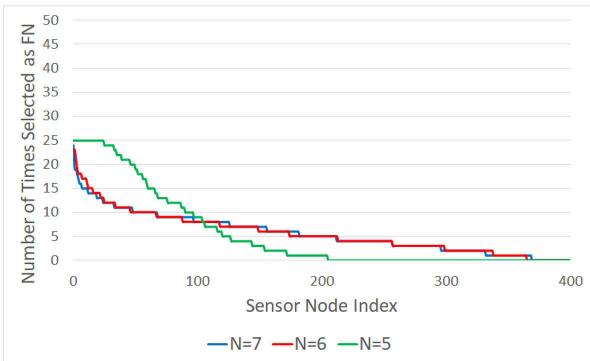


(b) Comparison for the proposed scheme.

Figure 3: The number of FNs at each trial



(a) Comparison for each scheme



(b) Comparison for the proposed scheme.

Figure 4: The number of times selected as FN