Self-organizing Wireless Sensor Networks Based on Biological Collective Decision Making for treating Information Uncertainty

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***Abstract*—Due to the rapid growth in scale and complexity of information networks, self-organizing systems have been focused on for realizing new network control architectures that have high scalability, adaptability, and robustness. However, in self-organizing systems, the uncertainty (incompleteness, ambiguity, and dynamicity) of information observable for components in the system can lead to the slow adaptation to environmental changes and the lack of a global optimality, which complicates a practical use of self-organizing systems in industrial and business fields. In this study, we adopt the principle of collective decision making, in which a coordinated decision in a group is achieved through local interactions of components, in order to realize a network control mechanism adaptable to such information uncertainty. Specifically, we apply Effective Leadership model, which is a mathematical model of collective decision making, to a self-organizing control mechanism. In Effective Leadership model, there are two types of individuals, informed and non-informed ones, and collective decision is achieved through local interaction of them. Through simulation experiments, we reveal the advantages and characteristics of the network control mechanism based on Effective Leadership model.**

***Index Terms*—Collective Decision Making, Potential-based Routing, Information Uncertainty, Bio-inspired Network Controlling**

1. Introduction

Because of the rapid growth in scale and complexity of information networks, self-organizing systems have been paid much attention for realizing new network architectures that have high scalability, adaptability, and robustness [1], [2]. In self-organizing systems, each component behaves autonomously only with simple rules and local information. As a result of local interactions of components, a global behavior or pattern emerges in a macroscopic level. By adopting the principle of self-organization, network control systems can be robust and adaptable to unexpected environmental changes. However, there is a significant problem for a practical use of self-organizing control systems in industrial and business fields. In information networks, information observable for each component is uncertain. That is, observable information is

- *dynamic* according to changing condition of nodes,
- *incomplete* because of the constraints of sensor nodes' capacity,
- *ambiguous* because of estimation/communication error.

Such uncertainty of observable information can lead to the slow adaptation to environmental changes and the lack of a global optimality of systems. To tackle this problem, we introduce the principle of *collective decision making* of swarms to network control mechanisms. This is because, in swarms of animals such as birds, fish, and insects, individuals can make a coordinated decision through local interactions among them although the perceptive ability of each component is limited (*incompleteness, ambiguity*) and its condition, e.g., the direction of the move, is changing dynamically (*dynamicity*) so that information which it has is uncertain.

In this study, we focus on Effective Leadership model [3] as a mathematical model of the behavior of collective decision making in swarms, and adopt it to realizing a network control mechanism that can work under information uncertainty. In Effective Leadership model, there are two types of individuals, *informed individuals* and *non-informed individuals*. On one hand, informed individuals are more experienced and well-informed than the others so that they have pertinent information, i.e., the preferred directions to move in. They have a role as leaders of the group to guide the other individuals to move in their own preferred directions. On the other hand, non-informed individuals have limited information and decide their direction to move in following individuals surrounding themselves. Consequently, informed individuals lead non-informed ones to move in the preferred decisions through local interactions among individuals, and, as a result, individuals can make a coordinated decision. In Effective Leadership model, as the group size (the number of individuals) becomes larger, the ratio of informed individuals to the whole group needed for the achievement of collective decision to all individuals in the group is smaller. This indicates that Effective Leadership model has high scalability to the size of groups.

We apply Effective Leadership model to self-organizing network control mechanisms to conquer information uncertainty. We take potential-based routing with an external controller proposed in [4] as an example of self-organizing network control mechanisms, and propose potential-based routing based on Effective Leadership model. In previous work [4], the authors introduce an external controller to potential-based routing for facilitating the adaptation speed to environmental changes. In the mechanism, an external controller monitors the state of a network and feedbacks control inputs to partial nodes called *controlled nodes*. Through local interactions among nodes, the influence of control feedback by the external controller expands all over the network. In other words, controlled nodes have a role to guide the other nodes to adapt to environmental changes quickly. In this study, we consider controlled nodes as *leader nodes* which guide the other nodes, which we call *follower nodes*, to make a coordinated decision. Leader and follower nodes correspond to informed and non-informed individuals in Effective Leadership model, respectively.

Through simulation experiments, we reveal the advantages and characteristics of the network control mechanism based on Effective Leadership model. First, we investigate the appropriate selection of leaders in network systems. In Effective Leadership model, individuals move continuously and their relative positions are dynamically changing. Therefore, we investigate how the selection of leaders affect to control efficiency when introducing to a static topology and reveal leader selections appropriate for faster adaptation to environmental changes. Second, we evaluate the performance of our proposed mechanism in wireless sensor networks. We evaluate our mechanism through simulations in environment considering constraints of wireless sensor networks, such as communication delay, packet loss and congestion, and prove that our mechanism has high scalability and work well under information uncertainty.

The remainder of this paper is as follows. First, in Section 2, we apply Effective Leadership model to network control mechanisms to deal with two information uncertainty while calculating control feedback. We propose potential-based routing based on Effective Leadership model. In Section 3, we evaluate our proposed method through simulation experiments and discuss the results. Finally, in Section 4 we describe conclusion and future work of this study.

2. Application of Collective Decision Making to Potential-based Routing

In this section, we take potential-based routing with the external controller that is proposed in previous work [4] as an example of self-organizing network control mechanisms. We apply Effective Leadership model [3], a mathematical model of collective decision making in swarms, to the mechanism.

We explain potential-based routing and its improvement, potential-based routing with the external controller, in Section 2.1 and Effective Leadership model in Section 2.2. Then, in Section 2.3, we propose potential-based routing which adopt the principle of Effective Leadership model.

2.1. Potential-based Routing

Potential-based routing is a self-organizing routing mechanism for wireless sensor networks [4]–[8]. In potential-based routing, data packets are forwarded in accordance with a *potential field*, a kind of gradient fields, which includes routing information. The potential-field emerges as a result of local interactions of nodes.

In potential-based routing, each node is assigned a scalar value called "*potential*." In general, a potential field is constructed so that a lower potential value is assigned to a nearer node from the sink node. Therefore, with a simple forwarding rule, "sending a data packet to a neighboring node with a lower potential value," data packets can be delivered to sink nodes. Because potentials of nodes are updated through local interactions among nodes, it is known that potential-based routing can work with low communication and calculation costs even in large-scale networks.

2.1.1. Potential Field Construction. Sheikhattar and Kalantari [6] focused on the convergence of potential-based routing and facilitated the potential convergence speed. They proposed a potential calculation method based not only on current potentials but also on last potentials to accelerate potential convergence. In this method, node i's potential $\theta_i(t)$ at time t is updated by (1).

$$\begin{aligned}\theta_i(t+1) &= (\alpha+1)\theta_i(t) - \alpha\theta_i(t-1)\\ &\quad + \beta\sigma_i\left(\sum_{k\in\mathcal{N}_b(i)}\{\theta_k(t)-\theta_i(t)\} + f_i(t)\right),\end{aligned} \tag{1}$$

where $\mathcal{N}_b(i)$ is a set of neighbors of node i. α is a parameter that determines the weight of current and last potential values when calculating the next potential value. Larger α means that the weight of the last potential value is larger and therefore the system becomes less subject to temporal noises and disturbance, while the convergence speed is slower. β is a parameter that determines of the weight of neighbor node potentials. In prior work [6], σ_i is defined as $\sigma_0/|\mathcal{N}_b(i)|$ (σ_0 is a parameter). In this study, we set σ_i to constant value σ ($0<\sigma<1$) since potentials diverge in some situations with $\sigma_i = \sigma_0/|\mathcal{N}_b(i)|$. $f_i(t)$ corresponds to the flow rate of node i at time t. For sensor node i, flow rate $f_i(t)$ is a positive value, which indicates the data generation rate of node i. For sink node i, flow rate $f_i(t)$ is a negative value, which implies the amount of data packets delivered to node i. If flow rates of nodes are set to satisfy $\sum_{n\in\{1,\cdots,N\}} f_n(t) = 0$, then a potential field is constructed such that the actual rates at which data packets are delivered to nodes satisfy the given flow rates. In this study, we set flow rates of sink nodes so

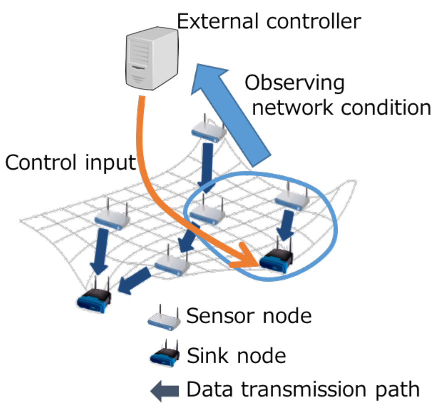

Figure 1. Potential-based routing with the external controller

that the numbers of data packets delivered to each sink node are equal for load balancing. In details, we set flow rates of sink nodes to the same value.

2.1.2. Potential Field Construction with the External Controller. In previous work [4], the authors introduced an external controller, which monitors and controls a system, into potential-based routing proposed in prior work [6] for facilitating the convergence speed of potentials.

The role of the external controller is to (i) collect potential information of a partial set of nodes (*observable nodes*), (ii) estimate potential values of the other nodes based on the potential dynamics model, and (iii) provide control feedback to another partial set of nodes (*controlled nodes*) to facilitate potential convergence as shown in Fig. 1. In potential-based routing with the external controller, the potential value $\theta'_i(t)$ of node i at time t is updated by (2).

$$\begin{aligned}\theta'_i(t+1) &= (\alpha+1)\theta'_i(t) - \alpha\theta'_i(t-1) \\ &+ \beta\sigma_i\left(\sum_{k\in\mathcal{N}_b(i)}\{\theta'_k(t)-\theta'_i(t)\} + f_i(t)\right) + \eta_i(t),\end{aligned} \quad (2)$$

where $\eta_i(t)$ corresponds to the control input provided to node i by the external controller. If node i is not controlled one, $\eta_i(t)$ is 0. Control inputs are calculated based on H^∞ control theory [4], [8].

In this study, we apply Effective Leadership model to potential-based routing with the external controller. We explain the details in Section 2.3.

2.1.3. Data Packet Forwarding. When a sensor node receives a data packet, it probabilistically determines the next hop node of it in accordance with potentials of itself and its neighbors. Probability $P_{i\to n}(t)$ that node i selects neighboring node $n \in \mathcal{N}_b(i)$ as the next hop node of the data packet at time t is calculated by (3).

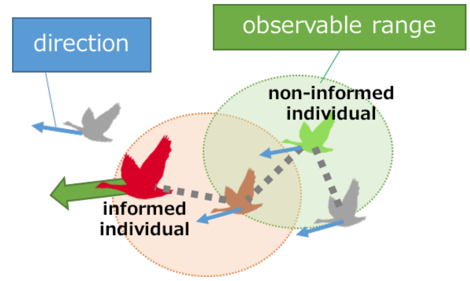

Figure 2. Overview of Effective Leadership model

$$P_{i\to n}(t) = \begin{cases} \frac{\theta_i(t)-\theta_n(t)}{\sum_{j\in\mathcal{N}_{low}(i)}\{\theta_i(t)-\theta_j(t)\}}, & \text{if } n\in\mathcal{N}_{low}(i) \\ 0, & \text{otherwise} \end{cases}, \quad (3)$$

where $\mathcal{N}_{low}(i)$ is a set of neighboring nodes of node i with lower potential than node i. Nodes with lower potentials are likely to receive a larger number of data packets.

2.2. Effective Leadership Model

Effective Leadership model [3] is a mathematical model of collective decision making in swarms. Figure 2 shows the overview of Effective Leadership model. In Effective Leadership model, there are two types of individuals, *informed individuals* and *non-informed individuals*. Informed individuals have information about their preferred directions, and decide their directions according to both social interactions with their neighbors and their own preferred directions. On the other hand, non-informed individuals decide their directions in accordance only with social interactions.

Individual i in a group has position vector $\mathbf{c}_i(t)$ and direction vector $\mathbf{v}_i(t)$ at time t. Individuals attempts to maintain a minimum distance $dist_\alpha$ from other individuals for avoiding collisions. When the distance between individual i and j is lower than $dist_\alpha$, individual i moves away from individual j. In details, desired direction $\mathbf{d}_i(t)$ of individual i at time t is determined by (4).

$$\mathbf{d}_i(t+\Delta t) = -\sum_{j\in\mathcal{N}_b(i,dist_\alpha)}\frac{\mathbf{c}_j(t)-\mathbf{c}_i(t)}{|\mathbf{c}_j(t)-\mathbf{c}_i(t)|}, \quad (4)$$

where $\mathcal{N}_b(i, dist_\alpha)$ corresponds to a set of individuals whose distances to individual i are lower than $dist_\alpha$.

If there are no other individuals within range $dist_\alpha$, a non-informed individual is attracted to individuals within range $dist_\rho$. $dist_\rho$ indicates the local interaction range of individuals. Non-informed individual i determines its desired direction $\mathbf{d}_i$ by (5).

$$\mathbf{d}_i(t+\Delta t) = \sum_{j \in \mathcal{N}_b(i, dist_\rho)} \frac{\mathbf{c}_j(t) - \mathbf{c}_i(t)}{|\mathbf{c}_j(t) - \mathbf{c}_i(t)|} + \sum_{j \in \mathcal{N}_b(i, dist_\rho)} \frac{\mathbf{v}_j(t)}{|\mathbf{v}_j(t)|}. \quad (5)$$

The first term of the right side of (5) corresponds to the vector from the position of individual i to the averaged position of neighboring individuals. This implies that non-informed individuals attempt to attract to neighboring individuals. The second term of the right side of (5) corresponds to the averaged direction of neighboring individuals. This implies that non-informed individuals attempt to align their directions with neighboring individuals.

On the contrary, informed individuals decide their desired directions based not only on social interactions but also on their preferred directions. Informed individual i has information about its preferred direction $\mathbf{g}_i$ and decides its desired direction $\mathbf{d}'_i(t)$ as time t by (6).

$$\mathbf{d}'_i(t+\Delta t) = \frac{\hat{\mathbf{d}}_i(t+\Delta t) + \omega_0 \mathbf{g}_i}{|\hat{\mathbf{d}}_i(t+\Delta t) + \omega_0 \mathbf{g}_i|}, \quad (6)$$

where $\hat{\mathbf{d}}_i(t)$ is the unit vector of $\mathbf{d}_i(t)$, i.e., $\hat{\mathbf{d}}_i(t+\Delta t) = \frac{\mathbf{d}_i(t+\Delta t)}{|\mathbf{d}_i(t+\Delta t)|}$. ω_0 is a parameter that determines the weight of preferred direction $\mathbf{g}_i$ when the informed individual decides its desired direction. In prior work [9], ω_0 is considered as "assertiveness" of individuals. If ω_0 is 0, informed individuals are not influenced by their preferred directions $\mathbf{g}$. The higher the value of ω_0 is, the larger the influence amount of preferred directions $\mathbf{g}$ to desired directions of informed individuals is.

2.3. Potential-based Routing Based on Collective Decision Making

In this paper, we applied Effective Leadership model for a process where each node in potential-based routing coordinates to form a potential field (Table 1). In the proposed mechanism, we consider controlled nodes as *leader nodes* that have a role of leaders that guide the other nodes just like informed individuals in Effective Leadership model. According to control feedback provided by the external controller, leader nodes can update their potentials for faster convergence of potentials. On the contrary, we consider non-controlled nodes as *follower nodes* that behave following their neighboring nodes just like non-informed individual. Through local interactions among leader/follower nodes, leader nodes guide follower nodes, which results in faster potential field construction. The overview of the proposed mechanism is shown in Fig. 3.

We explain the potential field construction in our proposal mechanism. On one hand, follower nodes update their potential values in accordance with local information, i.e., potential values of itself and neighbors, using (1). On

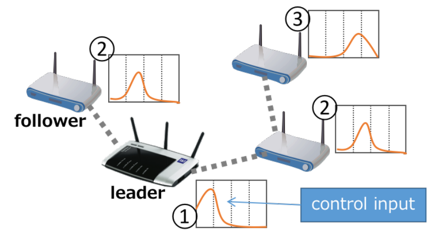

Figure 3. Potential-based routing based on Effective Leadership model

the other hand, leader nodes update their potential values based not only on local information but on control feedback provided by the external controller. Potential value $\theta''_i(t)$ of leader node i is updated using $\theta_i(t)$ by (7).

$$\theta''_i(t) = (1-\omega)\theta_i(t) + \omega g_i(t), \quad (7)$$

where $g_i(t)$ is the preferred potential value of leader node i. ω $(0 < \omega < 1)$ is a parameter corresponding to ω_0 in Effective Leadership model, which represents the strength of the tendency of leader individuals to lead the swarm in (6), and it is the weight for the target potential $\mathbf{g}_i(t)$. Preferred potential value $g_i(t)$ is calculated using control feedback $\eta_i(t)$ provided by the external controller by (8)

$$g_i(t) = \theta_i(t) + \eta_i(t). \quad (8)$$

Control feedback by the external controller is calculated so that the potential field converges to the target potential field $\bar{\mathbf{\Theta}} = \{\theta_1, \cdots, \theta_N\}$ in a short time.

When a sensor node receives a data packet, the node probabilistically selects the next hop node of the data packet by using (3).

3. Simulation Experiments

In order to find a clue of applying Effective Leadership model to the network and to evaluate the performance of the proposed mechanism against information uncertainty, we performed following two kinds of simulations.

First, in Section 3.1, we quantitatively evaluated the relationship between the performance, and the number and the positions of leader nodes through numerical simulation using MATLAB. Through these experiments, we also investigated leader selection that fascinates the potential-field construction. In previous work [3], the authors consider individuals in a group move dynamically and fluidly changing their position without static topology, therefore we made an investigation into the selection of leaders in a topology.

Second, we evaluated the performance of the proposed mechanism assuming wireless sensor networks where each node behaves asynchronously. We averaged the time steps of 5 trials in the following all simulations. In Section 3.2, we conducted simulation experiments assuming that the external controller can observe potential information of

TABLE 1. THE CORRESPONDENCE OF EFFECTIVE LEADERSHIP MODEL AND POTENTIAL-BASED ROUTING

Effective Leadership model	Potential-based routing
A group of various individuals with different preferences and abilities	A network composed of various kinds of nodes with different technical standards and performances
Leader individuals having more information than the others	Leader nodes receiving control inputs from the external controller
Non-informed individuals	Follower nodes
Position information $\boldsymbol{c}$ of an individual and its neighboring individuals	Potential information θ of itself and neighboring nodes
Direction information $\boldsymbol{v}$ of an individual and neighboring individuals	The changing amount of potential of a node
Target direction $\boldsymbol{g}$	Target potential values $\boldsymbol{g}$
Accuracy of the direction to move in	Convergence time steps of the potential-field

all nodes without any communication delay for revealing the advantages and properties of the proposed mechanism. Actually, in real network environment, it is difficult for the controller to observe all information in the network and the information include communication delays. As a result, observable information become uncertain. We then, in Section 3.3, evaluated the performance of the proposed mechanism in the case where observable information of the external controller is dynamic and incomplete. Specifically, we assumed that the external controller can observe potential information of a partial set of nodes, observable nodes, via sink nodes with communication delays. As a result, the proposed mechanism proved high scalability from the results of above 2 simulations in Section 3.1 and Section 3.2.

Third, in Section 3.3, we took errors in control caused by uncertain information into consideration through simulation that the controller can acquire information of a bounded scope. As a result, the proposed mechanism proved robustness against information uncertainty.

3.1. Relationship between the performance and the number and the positions of leader nodes

Considering to apply Effective Leadership model to network control, the number and positions of the leader nodes become important because in previous work [3] the authors didn't consider individuals have static topologies like networks. From the viewpoint of cost, it is desirable that the number of leader nodes with higher performance be smaller, it is also necessary to clarify the selection of the leader nodes for that purpose. In particular, in Effective Leadership model [3], it is shown that as the size of the swarm (the number of individuals) is larger, appropriate action can be taken by the group as a whole by a small proportion of leader individuals. If a similar tendency is found when corresponding Effective Leadership model to network control, we can consider it to be useful for application to a large-scale network. Therefore, in this section, we investigated the relationship of the number and positions of leader nodes with the control performance of the external controller [4].

In [4], [8], using potential-based routing which is a self-organizing route control method, authors achieved to improve convergence speed to the target potential by introducing an external controller that observes network information and performs control feedback. They revealed that the positions and the number of nodes (controlled nodes) which receive control feedback, affects the convergence speed (control performance of the controller). In this section, we regarded controlled nodes as leader nodes, investigated the relationship between the number and the positions of leader nodes and control performance of the controller, and obtained knowledge about the number and positions of appropriate and efficient leader nodes. In addition, as a result, the proposed mechanism showed high scalability that is similar in previous work [3].

The external controller is designed based on H_∞ control [10] and it is calculated using MATLAB's $dhinflmi$ function. This function gets control parameters as input that are set to achieve the control target according to the network topology and the positions of the leader nodes and returns outputs of the optimum H_∞ performance γ_{opt} and the controller transfer function G. The transfer function G as output satisfies the following two conditions:

- The system is stable and even when instantaneous disturbance is given to a system in equilibrium, the system returns to equilibrium again with the lapse of time.
- The closed loop norm of the controller $||G||_\infty$ is smaller than γ_{opt}.

Here, the closed loop norm of the controller $||G||_\infty$ represents the maximum value of the controller gain (ratio of output to input), the smaller the value of γ_{opt}, the smaller the gain. That is, the ability to suppress input disturbance and converge the system to equilibrium is high. In the proposed mechanism, the input to the controller is the deviation between the target potential and the current potential, since the output from the controller corresponds to the deviation between the target potential and the potential obtained as a result of the control. The smaller the value of γ_{opt}, the higher the ability to converge the potential to the target value and the robustness against noise and errors. In other words, the higher the degree of contribution of the leader nodes to the improvement of the control performance, the smaller the value of γ_{opt}. In this research, the value of γ_{opt} is used as an index to measure the control performance of the controller.

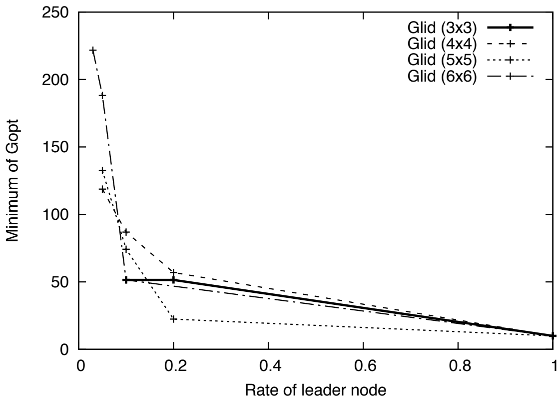

Figure 4. Relationship between the ratio of leader nodes in the network and $\mathrm{G_{opt}}(\gamma_{opt})$

We investigated the relationship with the control performance of the controller by calculating the value of γ_{opt} for all possible number and positions of leader nodes. We used lattice-shaped topologies that the sizes were 3×3, 4×4, 5×5 and 6×6, and set the ratio of leader nodes to all nodes to 0.025, 0.05, 0.1, 0.2, 1.0. For each network size, leader node percentage, we calculate γ_{opt} for all leader node patterns and the network size. Figure 4 represents the minimum value of γ_{opt} for each percentage of leader nodes.

From the result of Fig. 4, we can say that the value of γ_{opt} decreases as the proportion of the leader node increases. From this, it is shown that the control performance of the controller increases as the ratio of the leader node increases. We can consider that the reason is that the control input propagates faster to the entire potential field. This will be verified later.

On the other hand, compared with the decrease in γ_{opt} when the leader node percentage changes from 0.025 to 0.2, the decrease in γ_{opt} when the leader node percentage changes from 0.2 to 1 is fairly small. From this we can say the less the ratio of leader nodes to all nodes the larger the change in control performance. This tendency becomes more prominent as the number of nodes increases (Fig.4).

Also, when the ratio of leader nodes is around 0.2, the value of γ_{opt} decreases as the network size increases from the network size of 3×3 to 5×5. This result shows the more the number of nodes, the higher control performance can be obtained with a smaller proportion of leader nodes. As shown in [3], when the size (number of individuals) of the group becomes larger, it gets more possible for the group as a whole to take appropriate action by a small proportion of leader individuals, and we achieved incorporating this benefit to network control, which leads high scalability.

Figure 5, 6 show the selection of leader nodes of the maximum (Fig. 6) and minimum (Fig. 5) case of γ_{opt} in the above simulation.

There are multiple position patterns of leader nodes where γ_{opt} is the maximum or minimum, this figure represents one of them. From Fig. 5, in the case where γ_{opt} is

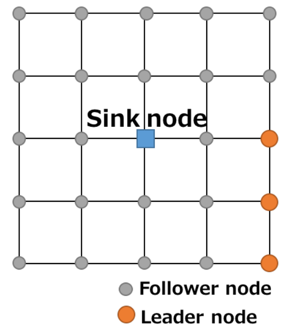

Figure 5. Leader selection that mimimizes γ_{opt}

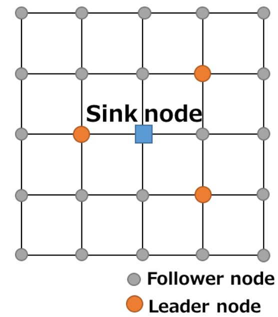

Figure 6. Leader selection that maximizes γ_{opt}

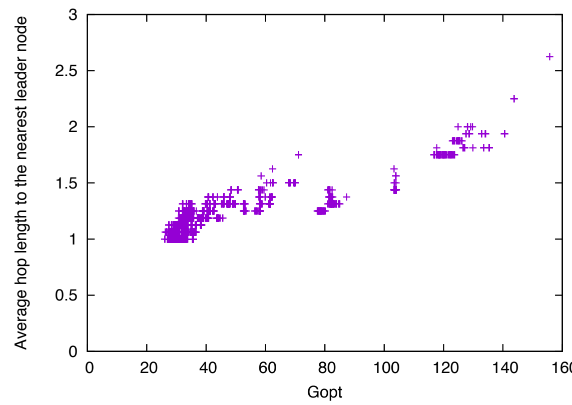

Figure 7. Correlation between the number of hops to the leader node and γ_{opt}

the maximum value, that is, where the control performance is lowest, the leader node is deployed on the edge of the network. In contrast, in the case where γ_{opt} is minimum and controller performs best (Fig. 6), leader nodes are deployed to be spread uniformly throughout the network. Also, Fig. 7 shows the relationship between the number of hops to the leader node and γ_{opt}. From this, it is said that the number of hop count to leader nodes has a great influence on γ_{opt}.

On the other hand, when setting the leader node, it is not cost-effective to determine the selection of leader nodes by calculate the average hop count of all nodes in the network because as the total number of nodes increases the computational complexity increases greatly. In this research, in order to select leader nodes uniformly across the field with light cost of calculation, we classify the network into clusters according to the number of leader nodes using the K-Means method and placed one leader at the center of one cluster. This solved the trade-off between the computational complexity and the control performance.

3.2. Properties of the proposed mechanism

In this section, based on the results in Section 3.1, we conducted evaluation in the wireless sensor network environment. We used square lattice-shaped topologies and

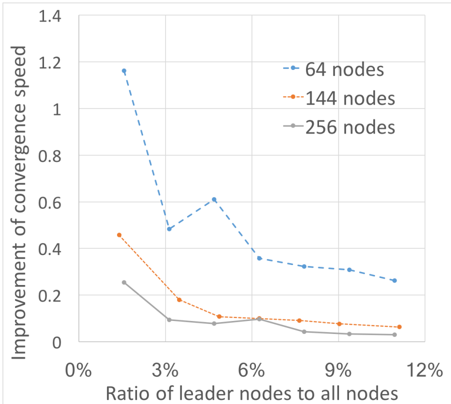

Figure 8. Relationship between the ratio of leader nodes in the network and the convergence time of potentials

the total number of nodes was set to 64 (8×8), 144 (12×12), 256 (16×16). In this simulation, the communication range of the node is set to 50m, and the nodes existing within the communication range are connected to each other. The number of sink nodes is set to 4 for the total number of nodes of 64, 6 for the case of 144, and 8 for the case of 256 total nodes.

In this evaluation, the leader node is set from 1% to 7% as a ratio with respect to the total number of nodes. We determined the positions of the leader nodes as we did in Section 3.1. The external controller [4] gives control feedback to the leader node at 50 second intervals. For simplification, this time, we exclude error in control feedback by assuming that the external controller can acquire the potential information of all the nodes without delay.

In this evaluation, immediately after the start of a simulation, potential information of all nodes begins to be updated and the external controller begins to control. Then, at 20 time steps after the start of the simulation, each sensor node starts transmitting data packets. The generation rate of the data packet in the sensor node located in the upper half of the grid network is 0.75 packet/time step, and the generation rate of data packets in the sensor node located in the lower half is 0.25 packet/time step. At this time, the external controller performs control so that the number of data packets received by each sink node becomes equal. After 200 time steps from the start of the simulation, the generation rate of data packets in each sensor node is changed upside down in the network. In this evaluation, after the data packet generation rate changes, the time until the potential field converges again is evaluated so that the number of data packets received by each sink node becomes equal. After changing the data packet generation rate, the generation rate of the data packet in the sensor node located in the upper half of the lattice network is 0.25 packet/time step, the generation rate of the data packet in the sensor node located in the lower half is 0.75 packet/time step. The simulation settings are shown in Table 2.

Figure 8 shows a graph plotting the relationship between network size, leader node ratio, and improvement of convergence speed of potential field. From Fig. 8, it was shown that as the ratio of the leader node is larger the time to converge becomes shorter, that is, the convergence performance improves as a whole. When the number of nodes is 64 and the ratio of the leader node is 0.047, and when the ratio of the leader node is 256 and the ratio of the leader node is 0.063, this trend is not applicable and the convergence time is prolonged, but this is caused by the occurrence of the oscillation due to the delay occurring when the control feedback propagates. However, although the convergence time itself is long, the generated oscillation is extremely fine without affecting the path control. From the above, there is a trade-off relationship between the ratio of the leader node and the convergence speed, and it is necessary to properly set the ratio of the leader node according to the control request.

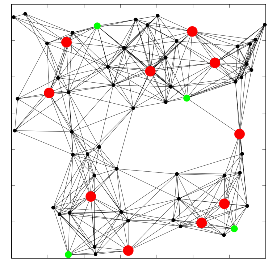

Figure 9. Example of randomly-positioned topology of 64 nodes

TABLE 2. NETWORK ENVIRONMENT IN THE SIMULATION EXPERIMENTS

Data	Value
The size of a data packet	128 bytes
The size of a control packet	30 bytes
The size of a ID packet	28 bytes
The size of an Ack packet	22 bytes
The number of buffer of a sensor node	1
The transmission interval of ID packets	1 sec
The potential update interval (1 step)	50 sec
The control interval of the external controller	50 sec

3.3. Performance evaluation in the case with dynamic and incomplete information

In this section, we examined the proposed mechanism from a viewpoint of robustness against uncertain information when control. In Section 3.2, the external controller calculated feedback input using global information without communication delay to exclude the error from the simulation. On the other hand, considering the real network environment, it might be better the external controller can calculate feedback by only uncertain information. In this evaluation, we investigated the potential convergence time after traffic changes in three cases: (i) the external controller can observe information of a partial set of nodes (nodes within one hop from sink nodes) with communication delay (observable information is dynamic and incomplete), (ii) the

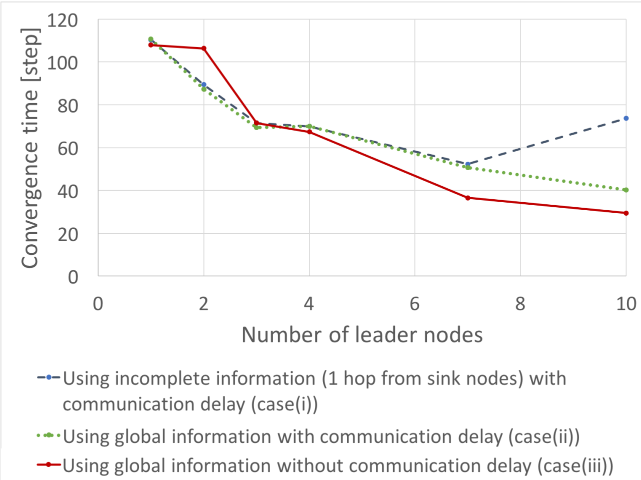

Figure 10. Comparison of convergence time steps

external controller can observe potential information of all nodes with communication delay (observable information is dynamic), and (iii) the external controller can observe potential information of all nodes without any communication delay (observable information is certain). Here, we used the network topology shown in Fig. 9, and leader nodes were selected using the same scheme as the evaluation in Section 3.2. The other settings, including the generation rate of data packets at sensor nodes and their changes, were following the evaluation in Section 3.2.

Figure 10 shows the potential convergence time in cases (i)–(iii). In Fig. 10, the vertical axis is time steps spent to potential convergence after traffic changes and horizontal axis is number of leader nodes in a 64-nodes randomly-positioned topology like of Fig. 9. The red solid line indicates the potential convergence time in case (i), the green dotted line indicates the result of using global information (2-hops range from sink nodes) with communication delay, and the blue dashed line indicates that in case (ii). Compared to case (iii), the convergence time in case (ii) is almost same or even less compared to the red solid line when the number of leader nodes are small (1–4) even with communication delays. Although the controller of case (i) can obtain information of only about 73% nodes in addition to the communication delay, the time steps are almost same or even less when the number of leader nodes is 1–4, or about 1–6% of all nodes. In the blue dashed line, the time steps spent to convergence increase when the number of leader nodes is 10, and the reason why this outlier occurs is currently under investigation.

4. Conclusion and Future Work

In this paper, we applied Effective Leadership model to self-organizing network control mechanisms and proposed potential-based routing based on Effective Leadership model for conquering information uncertainty. Through simulation experiments, we investigated the relationship among the network size (the number of nodes), the ratio of leader nodes, and the acceleration of the adaptation speed to environmental changes. Simulation results showed that as the number of nodes increases, a lower ratio of leader nodes is needed to facilitate the adaptation speed. Moreover, we showed that the acceleration amount of the adaptation speed deeply depends on the average distance between nodes and their own nearest leader nodes.

As future work, we will consider another information uncertainty that information become ambiguous because of error or noise in communication. we will investigate the relationship among the network size (the number of nodes), the ratio of leader nodes, and the acceleration of the adaptation speed in cases with more complicated network topologies such as random networks and small world networks. Then, we develop a network control mechanism conquering information uncertainty and prove its advantages.

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