Master's Thesis

Title

Conquering Information Uncertainty by Biological Collective Decision Making for Self-Organized Networks

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Abstract

Due to the rapid growth in scale and complexity of information networks, a new network architecture which has high scalability, adaptability, and robustness is needed. In large-scale and complicated information networks, it takes too much cost to keep monitoring states of all devices and controlling them. Therefore, it is essential for each device to autonomously consider, make a decision, and act only based on uncertain (incomplete, ambiguous, and dynamic) information. To tackle this problem, we apply the mechanism of collective decision making of swarms to network control mechanisms. In swarms of such as birds, fish, and insects, individuals can make a coordinated decision through local interactions of them although the perceptive ability of each component is limited so that information which it has is uncertain.

We focus Effective Leadership model, which is a mathematical model of collective decision making of swarms of such as birds, fish, and insects. In this model, a group consists of non-informed individuals, which attempts to follow neighboring individuals, and informed individuals, which are well-informed and therefore have the ability to make an appropriate decision. Through local interactions of such individuals, the group accordingly make a coordinated decision. Moreover, it is known that as the group size is smaller, a fewer informed individuals are needed to guide the group to make a coordinated decision, which implies high scalability.

In this study, we take potential-based routing with an external controller as an example of self-organizing network control mechanisms, and apply Effective Leadership model to it. We consider nodes controlled by the external controller as leader nodes that guide the other nodes like informed individuals do non-informed individuals. Through simulation experiments, we investigate the relationship among the network size, the ratio of leader nodes, and the adaptation speed to environmental changes.

Keywords

Collective Decision Making

Potential-based Routing

Information Uncertainty

Bio-inspired Network Controlling

Contents

List of Figures

List of Tables

1 Introduction

The Internet originated from ARPANET are rapidly expanding as the development of device and communication technologies, and becomes an increasingly important infrastructure. However, the Internet remains to be based on the conventional architecture although the Internet is continually growing, and various types of communication services/applications based on it are developed day by day. This reduces the durability and controllability of network systems. Especially, in recent years, various "things" such as sensors, actuators, electric grid, smartphones, vehicles, and electrical appliances communicate with each other with wired or wireless communications to be a network (Internet of things; IoT [1–3]). It is said that billions of devices will be connected to construct a network in the future [1]. As the scale and complexity of information networks grow, it becomes more and more difficult to monitor and control the entire networks. This means that the conventional network control mechanisms such as central control and distributed control based on global information is not adoptable. Therefore, we need to develop a new network architecture which has high scalability, adaptability and robustness.

For realizing a new network architecture, much attention is paid on self-organizing systems [4, 5]. In self-organizing systems, each component behaves autonomously with simple rules using only local information. Then, a global behavior or pattern emerges in a macroscopic level as a result of local interactions of components. By adopting the principle of self-organization, network control systems can be robust and adaptable to unexpected environmental changes. However, there are some problems that complicate the implementation of self-organizing network control mechanisms in the industrial field. Our goal is to develop a self-organizing network architecture for large-scale and complicated information networks.

In large-scale and complicated information networks, it takes too much cost to keep monitoring states of all devices and controlling them. Therefore, it is essential for each device to autonomously consider, make a decision, and act only based on uncertain (incomplete, ambiguous, and dynamic) information. To tackle this problem, we apply the mechanism of *collective decision making* of swarms to network control mechanisms. In swarms of such as birds, fish, and insects, individuals can make a coordinated decision through local interactions of them although the perceptive ability of each component is limited so that information which it has is uncertain.

In this study, we focus on Effective Leadership model [6], a mathematical model of the behavior of collective decision making in swarms. An animal group that forage or travel make decisions which direction to move through social interactions among the group. In the Effective Leadership model, there are two types of individuals, *informed individuals* and *non-informed individuals*. Informed individuals are experienced and well-informed so that they have pertinent information, such as knowledge about the location of a food source and of a migration route. They have a role as leaders of the group to navigate other individuals to their own preferred directions. Non-informed individuals have limited information and make a decision based on individuals surrounding themselves. Informed individuals lead non-informed ones to preferred decisions through local interactions of individuals, and as a result, individuals can make a coordinated decision. In Effective Leadership model, as the group size (number of individuals) becomes larger, a smaller proportion of informed individuals are needed to guide the group to a preferred direction, which leads to scalability to the size of groups.

In this study, we apply Effective Leadership model to self-organizing network control mechanisms to conquer information uncertainty. We take potential-based routing proposed in [7] as an example of self-organizing network control mechanisms, and proposed potential-based routing based on Effective Leadership model. In [7], the authors introduce an external controller to potential-based routing for facilitating the adaptation speed to environmental changes. In the method, the external controller monitors the state of the network and feedback control inputs to partial nodes called *controlled nodes*. Through controlled 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 fast. In this study, we consider control nodes as *leader nodes* which guide the other nodes to make a coordinated decision like informed individuals [6], and apply Effective Leadership model to potential-based routing with the external controller. Through simulation experiments, we investigate the relationship between the network size, the ratio of leader nodes, and the adaptation speed to environmental changes.

The remainder of this paper is as follows. First, in Chapter 2, we introduce related work on self-organization and collective decision making. Then, in Chapter 3, we apply Effective Leadership model to network control mechanisms. We take potential-based routing, and propose potential-based routing based on Effective Leadership model. In Chapter 4, we evaluate the proposed mechanism through simulation experiments and discuss the results. Finally, in Chapter 5 we describe conclusion and future work of this study.

2 Related Work

2.1 Self-Organized Biological Mechanisms and Their Applications

Self-organizing systems seen in the natural world, etc., each component of the system creates function in bottle-up manner based only on local interactions, and it is possible to realize high flexibility, adaptability, scalability, fault tolerance etc. In particular, the system of living organisms can acquire and develop functions suitable for the environment while encompassing the possibilities of various evolution, and can skillfully deal with environmental changes, and also in terms of the engineering application of the mechanism, many researches have been conducted in various fields [4, 5, 7–12].

An organism does not simply decide its own behavior based on only information at a certain point of time, predicting the future state from the information observed from the past to the present, it is known that organisms use prediction to determine their own behavior. In the literature [11], a group of birds fly in parallel flying as a theme, the authors introduce model predictive control to self-organizing system and discuss usefulness of prediction. In the literature [12], the authors introduce a model applying ant colony optimization algorithm, to optimize for multiple objective functions such as network delay, energy consumption, packet loss rate on routing. Also, in the document [13] the authors are investigating the outline of Firefly Algorithm inspired by synchrotron radiation of fireflies and trend of research using Firefly Algorithm.

2.2 Collective Decision Making

In a group of a social organisms, despite autonomously acting on the basis of limited information perceivable by each individual, the group as a whole is making a choice of behavior according to the condition of the environment and the group. Collective decision making is a very important issue for organisms with social nature who behave in a group. In order to act better as a means, each individual needs to acquire accurate information, but in the real world, in many cases, the information obtained by each individual is inaccurate and often enough information cannot be obtained for decision making. In addition, the confliction of individuals' objective due to differences in individual demand or preference, it becomes a cause of impeding the decision making as a group.

In the literature [14], in the situation where such information inaccuracy, individual confliction exists, the authors are investigating research which is discussing how collective decision making will be made. In situations where the information obtained is uncertain, by sharing information among individuals, it becomes possible to select the correct behavior. Sharing such information can be seen in creatures of various social nature, such as migration of honey bees and ants.

In the document [15] it is shown that the advantage of information sharing is improved by the presence of confliction among individuals and the correctness of decision making improves. In this paper, in particular, on the correctness of decision making in situations where collective decision making is performed while individuals who select actions to avoid false positives compete with individuals who select behavior to avoid false negatives Discussion, and verification.

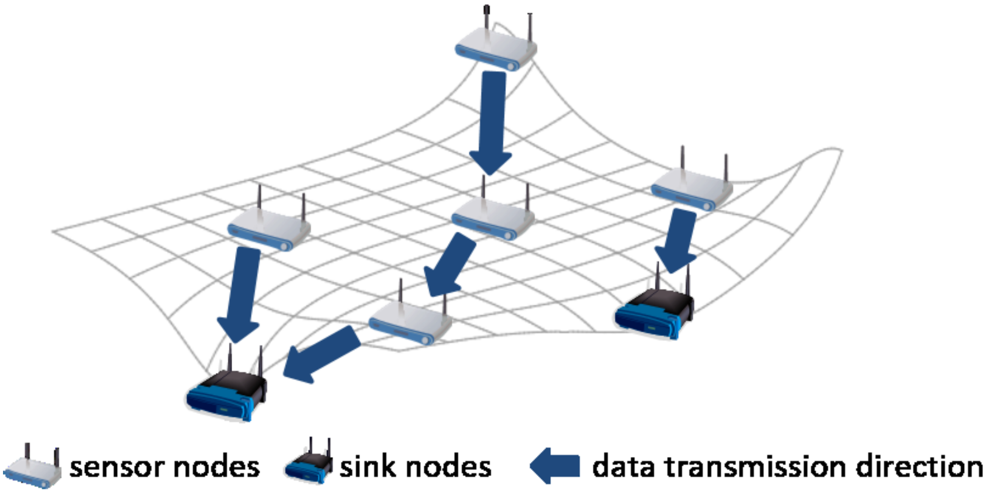

Figure 3.1: Potential-based routing

3 Application of Collective Decision Making to Potential-based Routing

In this chapter, we take potential-based routing with the external controller [7] as an example of self-organizing network control mechanisms. Then, we apply Effective Leadership model [6], a model of collective decision making in swarms, to it.

We explain potential-based routing and its improvement, potential-based routing with the external controller, in Subsection 3.1 and Effective Leadership model in Subsection 3.2. Then, in Subsection 3.3, we propose potential-based routing which adopt the principle of Effective Leadership model.

3.1 Potential-based Routing

Potential-based routing is a self-organizing routing mechanisms for wireless sensor networks [7–10, 16]. In potential-based routing, data packets are forwarded in accordance with a *potential field*, a kind of gradient fields, which includes routing information and 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 the fewer hops from the sink node a node is, the lower the potential value assigned to the node is. Therefore, with a simple forwarding rule, "sending data packets to neighboring nodes with lower potential," data packets arrive at sink nodes (Figure 3.1). 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 cost even in large-scale networks.

3.1.1 Potential Field Construction

Sheikhattar and Kalantari [16] focused on the convergence of potential-based routing and achieved enhancement of 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 at time t, $\theta_i(t)$ is calculated by Equation (1).

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

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 current noise, though the convergence speed is slower. β is a parameter that determines of the influence amount of neighbor node potentials. In [16], 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 $\sigma (0 < \sigma < 1)$ since potentials diverge in some situations with $\sigma_i = \sigma_0/|\mathcal{N}_b(i)|$. $f_i(t)$ corresponds to the amount of in/out flow of node i at time t. For sensor node i, flow $f_i(t)$ is a positive value, and it indicates the data generation rate of node i. For sink node i, flow $f_i(t)$ is a negative value, and it implies the amount of data packets delivered to node i. Global flow distribution is achieved by appropriately setting flow values at sink nodes. In details, by setting the flow value of each sink node to the same value, a potential field with which the number of data packets delivered to each sink node is approximately equal is constructed.

The convergence speed based on Equation (1) is faster than simple Jacobi iterations (such as [9]), but still takes a long time to converge due to its calculation being based only on local information.

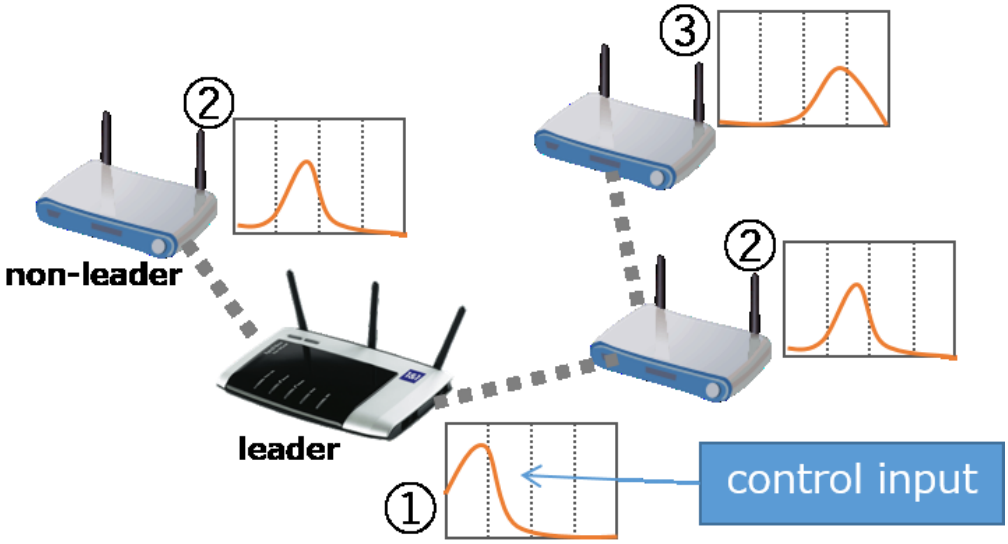

Figure 3.2: Potential-based routing with the external controller

3.1.2 Potential Field Construction with the External Controller

In [7, 7], the authors introduced an external controller, which monitor and control systems into potential-based routing proposed in [16] for facilitating the convergence speed of the potential field.

An external controller (1) collects information of potential values of partial nodes, (2) estimates potential values of the other nodes based on the potential dynamics model, and (3) feedbacks control inputs to partial nodes, which we call *controlled nodes*, to facilitate potential field convergence (Figure 3.2). In controlled node i, potential value $\theta_i(t)$ at time t is calculated by Equation (2).

$$\theta_i(t+1) = (\alpha+1)\theta_i(t) - \alpha\theta_i(t-1) + \beta\sigma_i \left(\sum_{k \in \mathcal{N}_b(i)} \{\theta_k(t) - \theta_i(t)\} + f_i(t) \right) + \eta_i(t), \quad (2)$$

where $\mu_i(t)$ corresponds to the control input which the external controller feedback to node i. Show [7, 8] for detailed explanation of how the external controller calculates control input $\mu_i(t)$.

In this study, we apply Effective Leadership model to potential-based routing with the external controller proposed in [7, 8]. We will explain the details in Subsection 3.3.

3.1.3 Data Packet Forwarding

When a node receives data packets, it determines the next hop node of data packets in a probabilistic manner in accordance with potentials of itself and its neighbors'. Each node i probabilistically determines the destination of the data packet based on the information on the potential of the node adjacent to itself. Probability $P_{i\to n}(t)$ that node i selects neighboring node $n \in \mathcal{N}_n(i)$ as the next hop node of a data packet at time t is calculated by Equation (3).

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

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.

3.2 Effective Leadership Model

Effective Leadership model [6] is a mathematical model of collective decision making in swarms such as birds, fish, and insects. For many species, a few experienced or well-informed individuals play an important role in decision making of the group. They have information about the locations where the group should move, e.g., the locations of a food source, and make their movement decisions based on the information. The other individuals, less experienced or informed individuals, move to the same direction with neighboring individuals so that they accordingly follow a few experienced or well-informed individuals. Consequently, the group achieves to make a coordinated decision.

In the Effective Leadership model, there are two types of individuals, *informed individuals* and *non-informed individuals*. Informed individuals decide their directions according to social interactions among the group and their own preferred directions. On the other hand, non-informed individuals make movement decisions only with social interactions. Figure 3.3 shows the concept of Effective Leadership model.

Individual i in the 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 α from other individuals for avoiding collisions. When the distance between individual i and j is lower than α, individual i moves away from individual j. In details, desired direction $\mathbf{d}_i(t)$ of individual i at time t is determined by Equation (4).

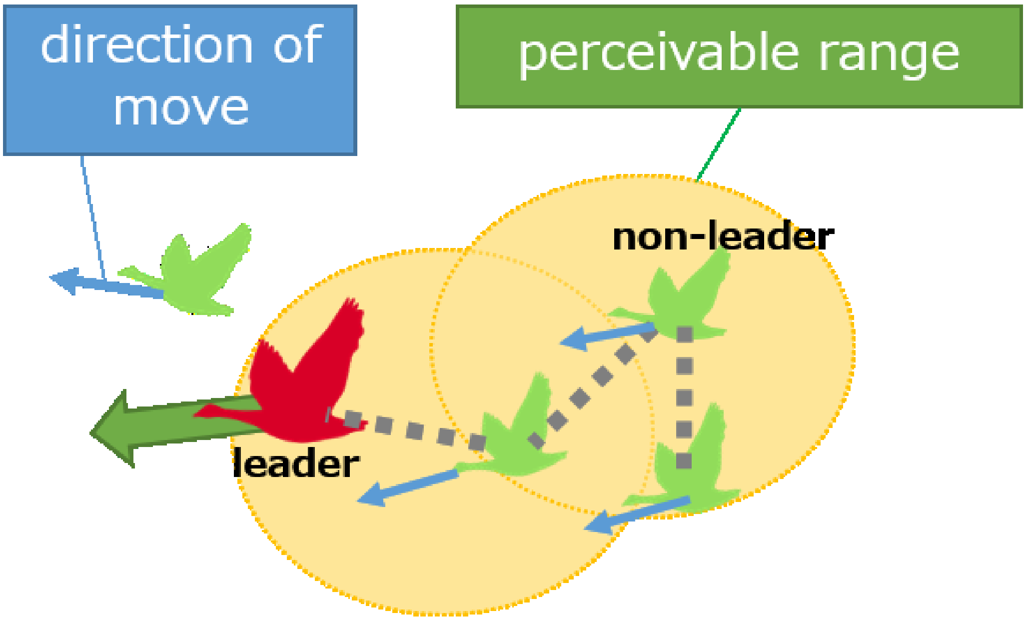

Figure 3.3: Effective Leadership model

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

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

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

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

The first term of Equation (5) corresponds to the average of position vectors of neighboring individuals. This implies that non-informed individuals attempt to attract to neighboring individuals as shown in Figure 3.4. The second term of Equation (5) corresponds to the average of direction vectors of neighboring individuals. This implies that non-informed individuals attempt to align its direction with neighboring individuals' as shown in Figure 3.5.

Leader individuals decide their desired directions based not only on social interactions but

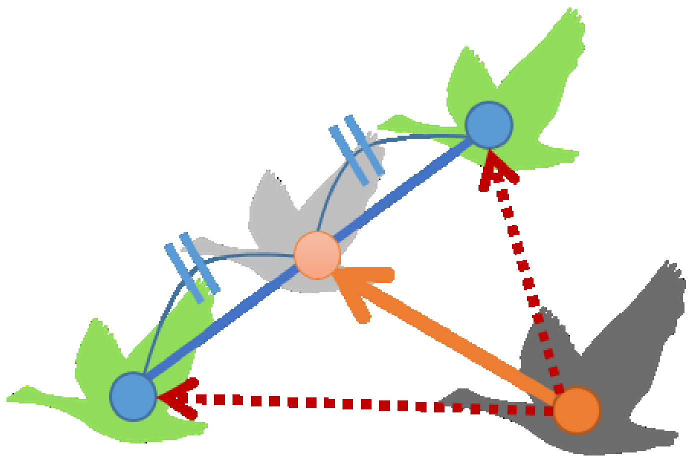
Figure 3.4: Attraction of positions

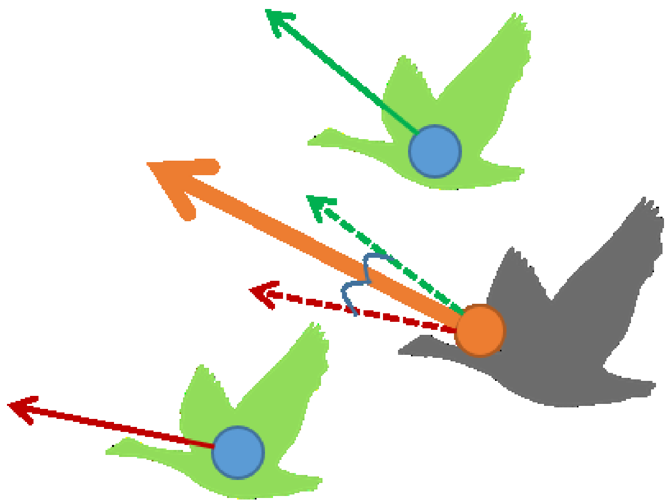
Figure 3.5: Alignment of directions

also on their preferred directions. Leader individual i has a preference to move in direction $\mathbf{g}_i$ and decides desired direction $\mathbf{d}_i(t)$ as time t by Equation (6).

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

where $\hat{\mathbf{d}}_i(t)$ is the unit vector of $\mathbf{d}_i(t)$. In other words, $\hat{\mathbf{d}}_i(t+\Delta t) = \frac{\mathbf{d}_i(t+\Delta t)}{|\mathbf{d}_i(t+\Delta t)|}$. ω_0 is a parameter that determines the weight of preferred direction $\mathbf{g}_i$ when leader nodes decide their desired directions. In [17], ω_0 is considered as "assertiveness" of individuals. If ω_0 is 0, leader nodes are not influenced by their preferred direction $\mathbf{g}$. The higher the value of ω_0 is, the larger the influence amount of preferred direction $\mathbf{g}$.

3.3 Potential-based Routing Based on Collective Decision Making

In this thesis, 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, using the expressions (1), (7), the potentials are updated of the non-leader node and the leader node. The non-leader node n updates its own potential $\theta_n(t)$ at time t using only the state and information of itself and the neighboring nodes (Expression (1)).

Leader nodes n have target potentials g, potentials are updated based on the target potential while coordinating with neighboring nodes (Formula (7)).

$$\begin{aligned}\theta_n(t) = \quad & (1-\omega)\Bigg\{\beta\sigma_n\Bigg(\sum_{k\in\mathcal{N}_b(n)}\{\theta_k(t-1)-\theta_n(t-1)\}+f_n(t-1)\Bigg)\\ + \quad & (\alpha+1)\theta_n(t-1)-\alpha\theta_n(t-2)\Bigg\}+\omega g_n(t).\end{aligned} \tag{7}$$

Here, 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 flock in the expression (6), and it is the weight for the target potential $\mathbf{g}_n(t)$.

The target potential $g_i(t)$ of the leader node is given by the following expression using the control feedback $\mu_i(t)$ by the external controller [7].

$$
\begin{aligned}
g_i(t) = \quad & \beta\sigma_n\Bigg(\sum_{k\in\mathcal{N}_b(n)}\{\theta_k(t-1)\theta_n(t-1)+f_n(t-1)\}\Bigg) \\
+ \quad & (\alpha+1)\theta_n(t-1)-\alpha\theta_n(t-1)+\mu_i(t). \qquad (8)
\end{aligned}
$$

The control feedback by the external controller is calculated so that the potential field converges to the convergence target $\bar{\mathbf{\Theta}} = \{\theta_1, \cdots, \theta_N\}$ in a short time. Through local interaction, the non-leader node follows the leader node that performs the potential update based on the control feedback, as a whole network, a potential field can be constructed quickly. The convergence target $\bar{\mathbf{\Theta}}$, The number of data packets received by each sink node is set to be equal.

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 nodes with different standards and performances
Leader individuals having more information than others	Leader nodes receiving control input
Non-leader individuals	Non-leader nodes
Position information of itself and perceivable neighboring individuals $\mathbf{c}$	Information on the potential of itself and neighboring nodes obtained by local interaction
Information on the direction of itself and perceivable neighboring individuals $\mathbf{v}$	Potential values 1 time step before and 2 time steps before the node
Target direction vector $\mathbf{g}$	Target potential values
Accuracy of the direction of travel	Convergence time of potential-field

4 Simulation Experiments

In order to obtain design guidelines for applying Effective Leadership model to the network, which mathematically modeled the mechanism of a process of decision making in a group, we performed numerical simulations and network simulations. First, in the 4.1 section, through numerical simulation, relationship between the number of leader nodes in the network, arrangement, network size, and the influence they have on network control will be investigated. In the 4.2 section, based on the findings obtained in the 4.1 section, the performance of control when applying Effective Leadership model to network is investigated through network simulation.

In the network simulation, we implemented in C ++, functions for Python networkx, scikit-learn package for graph operation, we also call MATLAB's $dhinflmi$ function for external controller design.

4.1 Number and Placement of Leader Nodes

In applying the Effective Leadership model to network control, the number and arrangement of the leader nodes becomes an important problem. 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 arrangement of the leader node for that purpose. In particular, in the literature [6], in the effective leadership model, it is shown that as the size of the flock (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 placement of leader nodes with the control performance of external controller [7].

In [7, 8], based 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 placement and the number of nodes (control nodes) giving control feedback, affects the convergence speed (control performance of the controller). In this section, the control node is made to correspond to the leader node, we investigate the relationship between and the number and the placement of control nodes and control performance of the controller, and obtain knowledge about the number and arrangement of appropriate leader nodes.

The external controller is designed based on H_∞ control [18] and it is calculated using MATLAB's $dhinflmi$ function. In this function, it was set to achieve the control target according to the network topology and the arrangement of the leader node outputs optimum H_∞ performance γ_{opt} and controller transfer function G, with control parameters as input. The transfer function to be output satisfies the following two conditions.

- The system is stable and 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 method, 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, robustness against noise and errors increases. In other words, the higher the degree of contribution to the improvement of the number of leader nodes and the control performance of placement, 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.

For the lattice network, calculate the value of γ_{opt} for each leader node number and arrangement, we investigated the relationship with the control performance of the controller. The size of the grid network is 3×3, 4×4, 5×5, 6×6, we set the ratio of leader nodes to 0.025, 0.05, 0.1, 0.2, 1.0. In Figure 4.1, for each network size, leader node percentage, we calculate γ_{opt} for all leader node patterns and calculate the network size, the Figure 4.1 represets the minimum value of γ_{opt} for each percentage of leader nodes is shown.

From the result of Figure 4.1, it can be confirmed 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. This is, by reducing the average

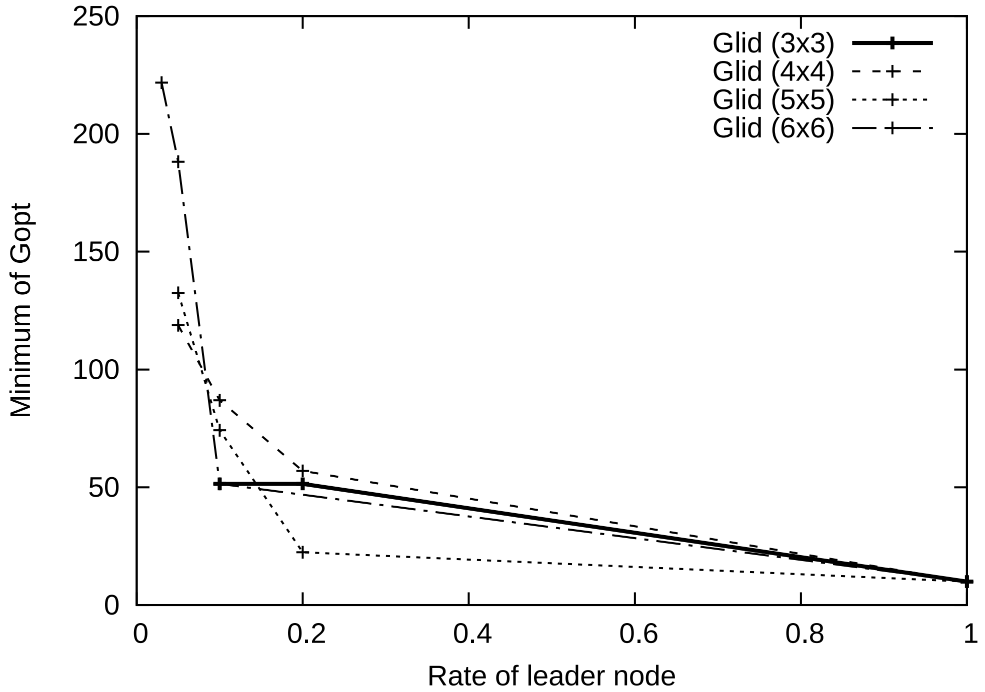

Figure 4.1: Relationship between the ratio of leader nodes and $\mathrm{G_{opt}}(\gamma_{opt})$

number of hops to the leader node receiving the control input from the controller 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, for the reduction of γ_{opt} until the leader node percentage changes from 0.025 to 0.2, the decrease in γ_{opt} until the leader node percentage changes from 0.2 to 1 is fairly small, in particular, this tendency becomes more prominent as the number of nodes increases. Also, when the ratio of leader nodes is 0.1, 0.2, focusing attention on the case where the network size is $4 \times 4 \sim 6 \times 6$, the value of γ_{opt} decreases as the network size increases, the higher the number of nodes, the higher control performance can be obtained with a smaller proportion of leader nodes. From this fact, the larger the size (number of individuals) of the group it is possible for the group as a whole to take appropriate action by a small proportion of leader individuals as shown in [6], and it can be applied also to network control, and high scalability to the scale of the network is expected. If the number of nodes is small, this trend does not apply to the result when the network size is 3×3, it is thought that the reason is that the influence due to the average hop count is small because the total number of nodes is small.

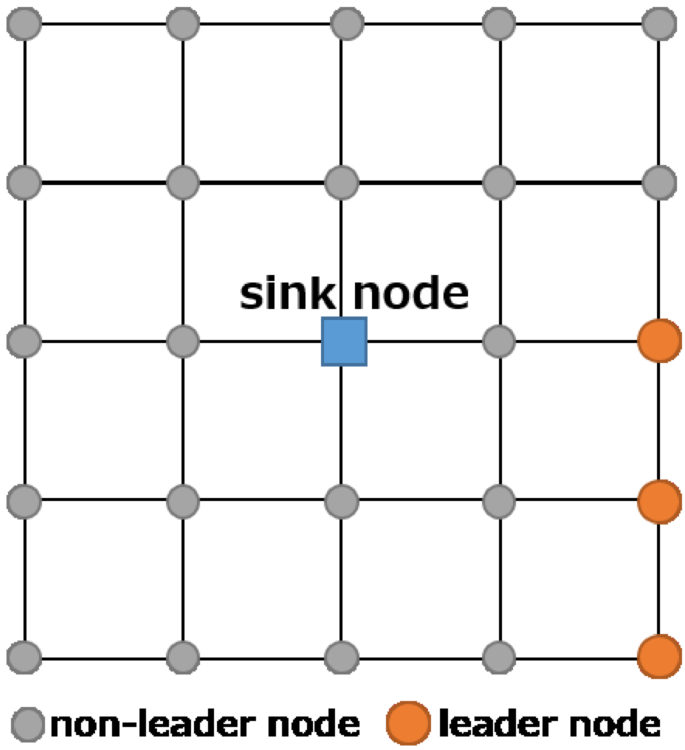

Figure 4.2: γ_{opt} minimized in lattice topology

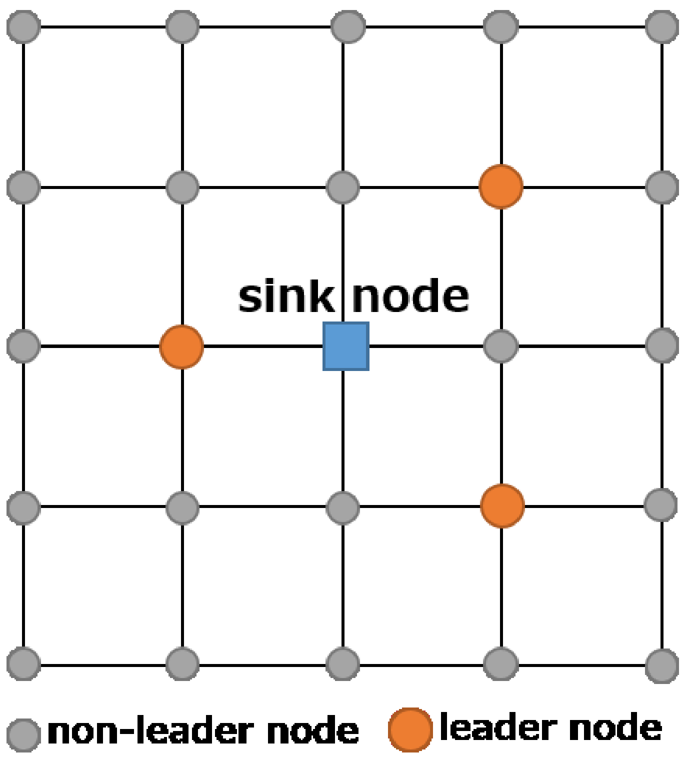

Figure 4.3: γ_{opt} maximized in lattice topology

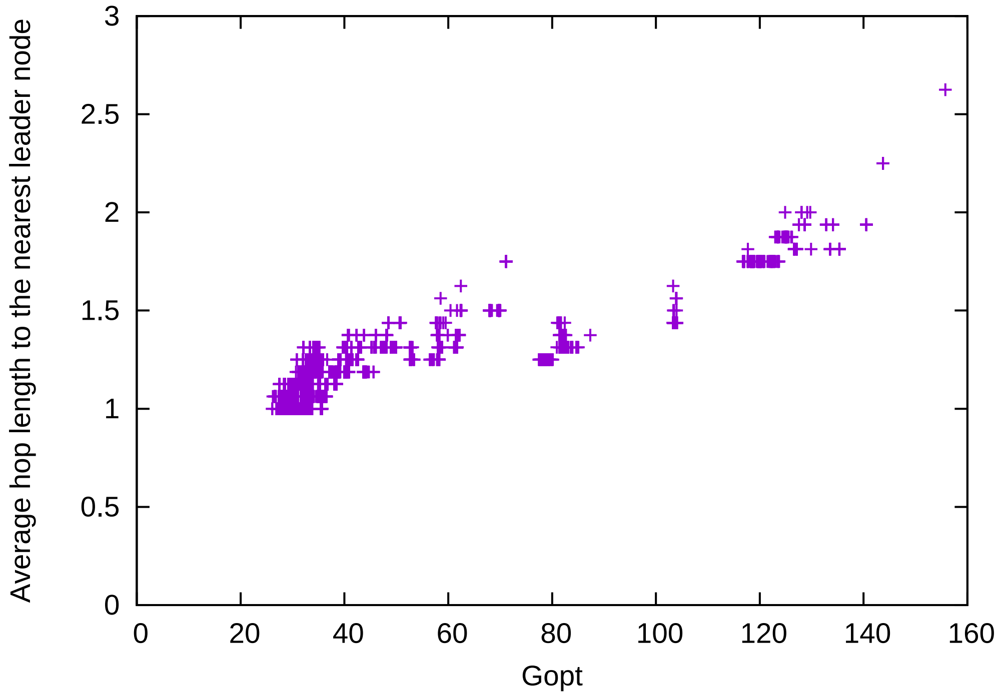

Figure 4.4: Correlation between the number of hops to the leader node and γ_{opt}

The Figure 4.2 and Figure 4.3 show that the value of γ_{opt} is the maximum in the above simulation, or the placement of the leader node in the case where it becomes minimum. There are cases where there are multiple settings of the leader node where γ_{opt} is the maximum or minimum, this figure represents one of them. From the figure, in the case where γ_{opt} takes the maximum value, that is, when the control performance is low, the leader node is arranged at the edge of the network, in the case where γ_{opt} takes the minimum value, it is arranged so that the leader nodes are spread evenly throughout. From this, about the value of γ_{opt}, that is, the performance of the controller, we can consider that the number of hops up to the leader node has an influence. Also, in the Figure 4.4, when the layout of the leader node is changed, it shows the relationship between the number of hops to the leader node and γ_{opt}. It can also be said from this figure that the control performance of the controller is greatly affected by the number of hops up to the leader node.

On the other hand, when setting the leader node, considering the average hop count of all nodes in the network, as the total number of nodes increases, it becomes less practical from the viewpoint of computational complexity. In this research, in order to arrange leader nodes evenly across the field, the network is classified into clusters by the number of leader nodes using the K-Means method, by setting the center based on the number of hops in each cluster to the leader node, the trade-off between the computational complexity and the control performance is solved.

4.2 Simulation Evaluation in Wireless Sensor Network

In this section, based on the results in Section 4.1, we conduct simulation evaluation in the wireless sensor network environment. The total number of nodes is set to 64, 144, 256 (Figure 4.7, 4.8, 4.9). In this evaluation, the communication range of the node is set to 50 m, and the nodes existing within the communication range are connected to each other. The sink node is set to 4 for the total number of nodes, 6 for the case of 144, and 8 for the case of 256 total nodes.

In this evaluation, the leader node is gradually changed from 1 to 7% as a ratio with respect to the total number of nodes, based on the findings obtained in the Section 4.1, the arrangement of the leader nodes classifies the field by the number of leader nodes by the K-Means method, one of the centers of each cluster is defined as a leader node. The external controller [7] gives control feedback to the leader node at 50 second intervals. For the sake of simplicity, it is assumed in this evaluation that the external controller can acquire the potential information of all the nodes without delay.

In this evaluation, the potential is updated immediately after the start of the simulation, and the control by the external controller is started. Then, at 1,000 seconds 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 0.015 packet / sec, and the generation rate of the data packet in the sensor node located in the lower half is 0.0050 packet / sec. At this time, the external controller performs control so that the number of data packets received by each sink node becomes equal. After 10,000 seconds from the start of the simulation, the generation rate of data packets in each sensor node is changed. In this evaluation, after the data packet generation rate changes, the time until the potential field reconverges 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 0.0050 peak / sec, the generation rate of the data packet in the sensor node located in the lower half is 0.015 packet / sec. The simulation settings are shown in Table 4.

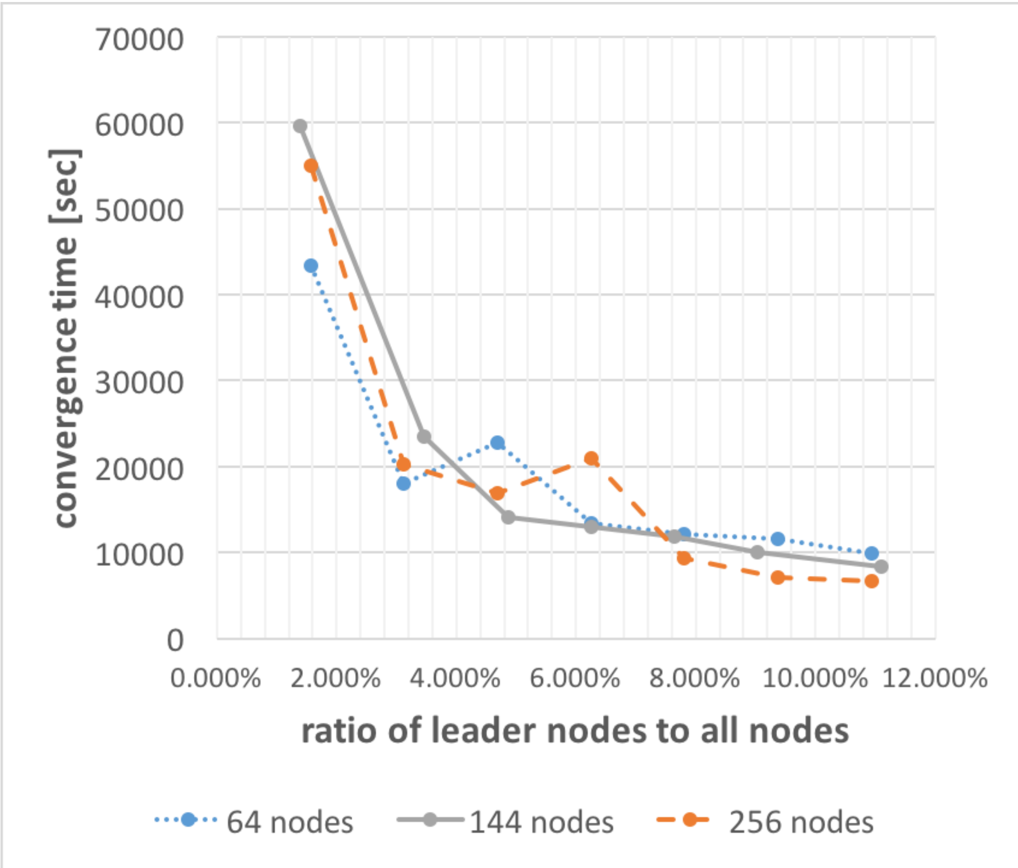

Figure 4.5: Relationship between ratio of leader nodes and convergence time

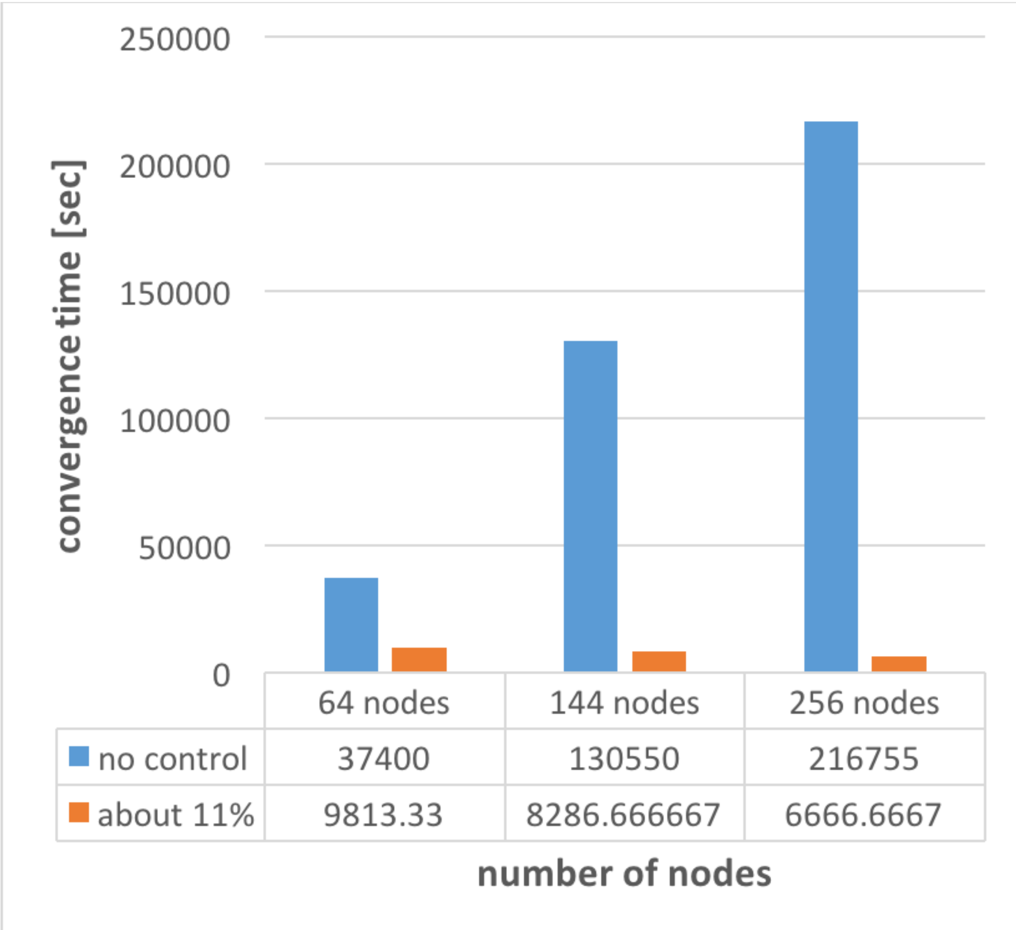

Figure 4.6: Comparison between proposed method and non-controlled method

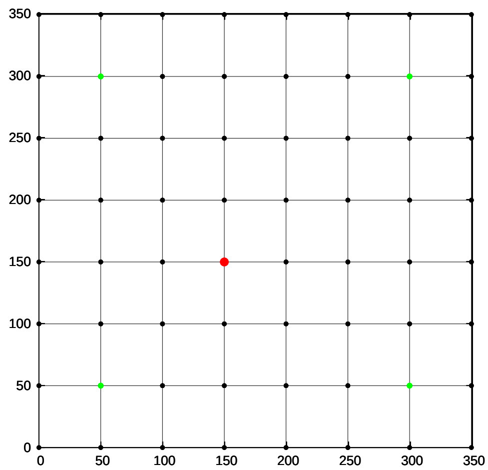

Figure 4.7: Example of topology of 64 nodes

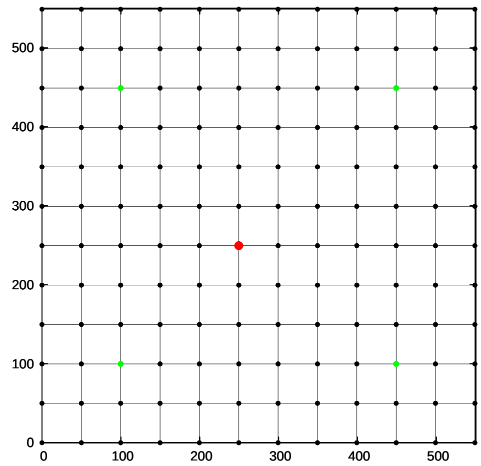

Figure 4.8: Example of topology of 144 nodes

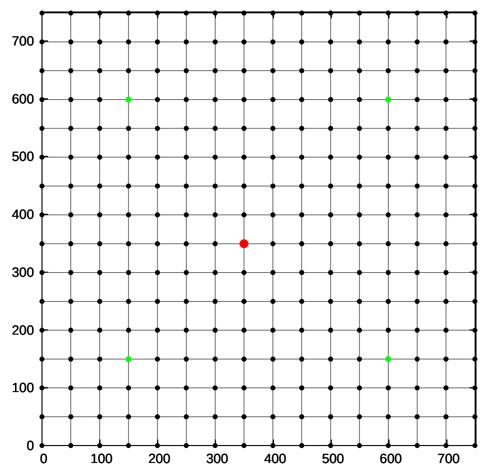

Figure 4.9: Example of topology of 256 nodes

Figure 4.5 shows a graph plotting the relationship between network size, leader node ratio, and potential field reconvergence time. From Figure 4.5, it was shown that as the ratio of the leader node is larger the time to reconvergence 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 reconvergence 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 reconvergence 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.

Table 2: Number of nodes and leaders

The number of nodes	The number of leader nodes	The percentage of leaders to all nodes
64 nodes	1 leader nodes	1.563%
	2 leader nodes	3.125%
	3 leader nodes	4.688%
	4 leader nodes	6.250%
	5 leader nodes	7.813%
	6 leader nodes	9.375%
	7 leader nodes	10.938%
144 nodes	1 leader nodes	0.694%
	2 leader nodes	1.389%
	4 leader nodes	3.472%
	7 leader nodes	4.861%
	9 leader nodes	6.250%
	11 leader nodes	7.639%
	13 leader nodes	9.028%
	16 leader nodes	11.111%
256 nodes	1 leader nodes	0.391%
	2 leader nodes	0.781%
	3 leader nodes	1.172%
	4 leader nodes	1.563%
	8 leader nodes	3.125%
	12 leader nodes	4.688%
	16 leader nodes	6.250%
	20 leader nodes	7.813%
	24 leader nodes	9.375%
	28 leader nodes	10.938%

Table 3: Field settings

The number of nodes	The number of sink nodes	The square measure of the field
64 nodes	4 sink nodes	$350 \times 350\ m^2$
144 nodes	6 sink nodes	$550 \times 550\ m^2$
256 nodes	8 sink nodes	$750 \times 750\ m^2$

Table 4: Network environment in the simulation experiment

Data	Value
The size of each data packet	128 bytes
The size of each control packet	30 bytes
The size of each ID packet	28 byte
The size of each Ack packet	22 bytes
The number of buffer of each sensor (non-sink) node	1
The transmission interval of ID packet	1 sec
The potential update interval	50 sec
The control interval	50 sec

5 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 hop length to the nearest leader node.

For future work, 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 mechanisms conquering information uncertainty and prove its advantages.

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