Self-organizing Control Mechanisms According to Information Confidence for Improving Performance

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***Abstract*—Self-organizing systems are focused on to realize novel network control systems that are highly scalable, adaptable, and robust. However, the uncertainty of information makes it difficult for self-organizing systems to work appropriately, thereby degrading their performance. It is necessary to improve the performance of self-organizing systems while retaining their advantages. Therefore, we apply the concept of flexible leadership of the collective decision-making in human groups to self-organizing control mechanisms. By incorporating this concept, agents dynamically and flexibly change their role (leader or follower) according to the confidence of their own information, which increases decision accuracy under information uncertainty. We propose a channel-selection mechanism based on collective decision-making in accordance with information confidence. Simulation experiments show that the proposed mechanism improves the performance of network systems while retaining the high adaptability.**

1. Introduction

Self-organizing systems are known to have high scalability, adaptability, and robustness [1], whereby they are applied to control large-scale and complex networks. The components of a self-organizing system behave automatically and autonomously on the basis of simple rules and local interactions among components, leading to the macroscopic emergence of global patterns or behavior. This bottom-up mechanism contributes to low communication and computational costs for such emergence. In practice, however, there are challenges to using self-organizing control systems in industrial and business systems [2].

In most actual self-organizing systems, the information available to components is uncertain (incomplete, vague, and dynamic) [3]. Generally, components have access to only local information (information incompleteness). Components often cannot access true information because of aspects such as noise or fluctuations (information vagueness). Previously collected information in dynamic systems can quickly become outdated (information dynamicity). Such uncertainty of information can lead components to sub-optimal or incorrect solutions, thereby degrading the performance of the systems. However, it still be a challenging task to improve the performance of self-organizing systems retaining their high scalability, adaptability, and robustness.

To tackle the challenge, we apply the *collective decision-making* of animal groups [4] to self-organizing systems. In groups of animals, perceivable information of individuals usually be uncertain. Despite the uncertainty of the perceived information, convergence to a state in which all individuals make an identically correct decision according to their conditions and surrounding environments is achieved through local interactions among individuals. Therefore, in the previous study [5], we have proposed a self-organizing channel-selection mechanism (CSM) based on collective decision-making according to information confidence in order to overcome the problem of information uncertainty.

In our proposal, we introduce the concept of *flexible leadership* [6] for collective decision-making in human groups. Human agents behave flexibly as leaders or followers in accordance with the confidence of their own information, which increases decision-making accuracy. Human agents with high confidence make decisions based on their own information, whereas human agents with low confidence attempt to follow the decisions of agents with high confidence. As a result, in a human group, agents with higher confidence act as leaders and guide the others.

To realize decision-making in accordance with information confidence, we also apply a method for integrating *individual information* (i.e., personal information based on aspects such as knowledge, experiences, and perceptive information) and *social information* (i.e., information obtained from other agents) according to information confidence [7]. Individual and social information are assumed to follow Gaussian distributions (i.e., $N(\mu, \sigma^2)$). The mean (μ) of a distribution is viewed as a judgment whereas the variance (σ^2) is viewed as the uncertainty of that judgment; in other words, lower variance indicates higher confidence of

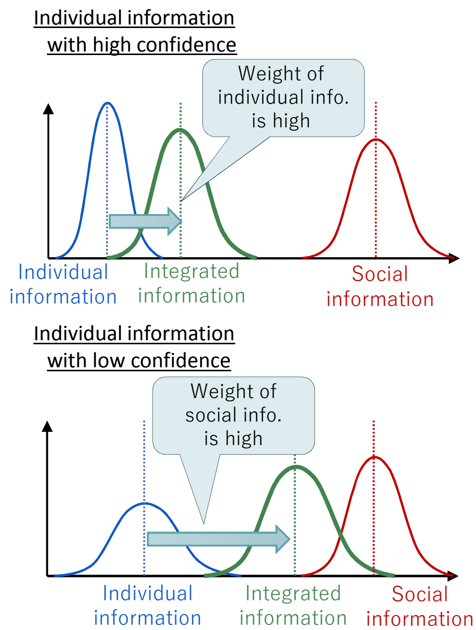


Figure 1. Integration of individual and social information

the judgment. Individual information and social information are then integrated according to their variables (see Figure 1). In a group, agents with lower confidence attempt to follow ones with higher confidence.

In our proposal, each node monitors a partial set of channels, estimates their quality, and calculates their confidence. The node shares this information with neighboring nodes and then integrate its own information and its neighbors' information considering their confidence. Finally, it selects a channel with high quality based on the integrated information. However, in the previous paper [5], we have not conducted simulation experiments for viewpoints of the performance of network systems under information uncertainty.

Therefore, we conduct simulation experiments for showing that introducing the concept of flexible leadership improves the performance under information uncertainty while retaining inherent advantages of self-organizing mechanisms. Specifically, in this paper, we focus on the adaptability, which is a significant feature of self-organizing mechanisms. The contributions of this paper are as follows:

1) We evaluate the performance of our proposal under information uncertainty. Especially, for investigating the influence of information vagueness, we evaluate our proposal in the case where nodes differ in the reliability of their own information. In this evaluation, we conduct simulation experiments in the environment assuming wireless sensor networks.
2) For clarifying the properties of our proposal, we investigate the influence of parameters in our proposal.

In Section 2, we propose and explain a CSM based on collective decision-making according to information confidence. In Section 3, we conduct simulation experiments to demonstrate the advantages and properties of our proposal. Finally, we conclude this study and mention possible future work in Section 4.

2. Channel Selection Mechanism According to Information Confidence

Each node estimates channel qualities based on collective decision-making and then selects a high-quality channel for data-packet forwarding. We here consider a channel to be of higher quality if its channel utilization is low.

Our proposal involves the following three steps: (1) Each node estimates channel qualities based on observable information. We refer to these estimated channel qualities as *individual information* (Section 2.1). (2) Each node obtains the individual information of neighboring nodes and then estimates channel qualities based on that information. We refer to these estimated channel qualities as *social information* (Section 2.2). (3) Each node integrates the individual and social information according to its confidence in its own information for selecting a high-quality channel (Section 2.3).

2.1. Channel Quality Estimation Based on Observable Information

Each node observes the channel states and then estimates the channel qualities based on the observed information. Node i ($\in \mathcal{N} = \{1, \cdots, N\}$) observes the partial set $\boldsymbol{c}_i(t)$ ($\subset \mathcal{M} = \{1, \cdots, M\}$) of channels at interval Δt_{obs} and checks their states, that is, whether each channel is busy or idle. By observing the channels, node i measures the idle-state ratio $v_{(i,j)}$ of channel j, measured as its time being idle in a time slot (Δt) relative to total time.

Node i estimates the quality of channel j based on the observed idle-state ratio $v_{(i,j)}$ of channel j. We define individual information as $p(D_v|D)$, where D_v corresponds to the estimated channel quality based on the observable information v and D corresponds to the true quality of the channel. We assume that the individual information for node i regarding channel j follows a Gaussian distribution with mean $\nu_{(i,j)}$ and variance $\tau^2_{(i,j)}$. In other words, individual information $p(D_v^{(i,j)}|D^{(i,j)})$ satisfies

$$p(D_v^{(i,j)}|D^{(i,j)}) \sim N(\nu_{(i,j)}, \tau^2_{(i,j)}). \tag{1}$$

The higher the distribution mean $\nu_{(i,j)}$, the higher the quality of channel j estimated by node i from the observable information. We consider the distribution variance $\tau^2_{(i,j)}$ as the uncertainty of the estimation. Note that the uncertainty of individual information depends on its confidence: higher uncertainty is reflected in lower confidence.

The distribution in (1) is updated in accordance with the observed information $v_{(i,j)}$ by the equations below:

$$\nu_{(i,j)} \leftarrow (1-\alpha)\nu_{(i,j)} + \alpha v_{(i,j)}, \tag{2}$$
$$\tau^2_{(i,j)} \leftarrow (1-\alpha)\tau^2_{(i,j)} + \alpha(1-\alpha)(\nu_{(i,j)} - v_{(i,j)})^2. \tag{3}$$

2.2. Channel-quality Estimation Based on Information Obtained from Neighboring Nodes

Each node obtains the individual information of its neighboring nodes through local interactions among nodes. It then estimates the channel qualities based on information obtained from its neighboring nodes. For node i, $\boldsymbol{s}_{(i,j)}$ corresponds to the information about channel j obtained from its neighboring nodes $\mathcal{N}_b(i)$. That is, $\boldsymbol{s}_{(i,j)} = \{(\nu_{(i,j)}, \tau^2_{(i,j)}) | i \in \mathcal{N}_b(i), j \in \mathcal{M}\}$.

Node i estimates the quality of channel j based on the information obtained from its neighboring nodes. We define social information as $p(D_s^{(i,j)}|D)$, where $D_s^{(i,j)}$ corresponds to the estimated channel quality based on the information from its neighboring nodes. We also assume that the social information for node i regarding channel j follows a Gaussian distribution with mean $\mu_{(i,j)}$ and variance $\sigma^2_{(i,j)}$. That is, social information $p(D_s^{(i,j)}|D^{(i,j)})$ satisfies

$$p(D_s^{(i,j)}|D^{(i,j)}) \sim N(\mu_{(i,j)}, \sigma^2_{(i,j)}). \tag{4}$$

The higher the distribution mean $\mu_{(i,j)}$, the higher the quality of channel j estimated by node i based on the information obtained from the neighboring nodes. The distribution mean $\mu_{(i,j)}$ is updated as

$$\mu_{(i,j)} \leftarrow \frac{\sum_{k \in \mathcal{N}_{conf}(i)} \nu_{(i,j)}}{|\mathcal{N}_{conf}(i)|}, \tag{5}$$

where $\mathcal{N}_{conf}(i)$ $(\subset \mathcal{N}_b(i))$ corresponds to the set of node i's neighboring nodes whose variance of individual information for channel i is lower than the threshold T_{τ^2}. In other words, the average social information is equal to the average channel qualities as estimated by the neighboring nodes with high confidence. For simplicity, we set $\sigma^2_{(i,j)}$ to a constant value σ_0^2 for all nodes and channels.

2.3. Integration of Individual and Social Information for Channel Selection

Each node integrates individual and social information according to information confidence, and selects a channel with high quality for data-packet forwarding.

By integrating individual information $p(D_v^{(i,j)}|D^{(i,j)})$ and social information $p(D_s^{(i,j)}|D^{(i,j)})$ according to their variances, node i estimates the quality of channel j.

Then, integrated information $p(D^{(i,j)}|D_v^{(i,j)}, D_s^{(i,j)})$ is estimated to follow a normal distribution:

$$p(D^{(i,j)}|D_v^{(i,j)}, D_s^{(i,j)}) \sim N\left(\phi_{(i,j)}, \rho^2_{(i,j)}\right). \tag{6}$$

The mean $\phi_{(i,j)}$ and variance $\rho^2_{(i,j)}$ are calculated by

$$\phi_{(i,j)} \leftarrow \frac{\tau^2_{(i,j)}\mu_{(i,j)} + \sigma^2_{(i,j)}\nu_{(i,j)}}{\tau^2_{(i,j)} + \sigma^2_{(i,j)}}, \tag{7}$$

$$\rho^2_{(i,j)} \leftarrow \frac{\tau^2_{(i,j)}\sigma^2_{(i,j)}}{\tau^2_{(i,j)} + \sigma^2_{(i,j)}}. \tag{8}$$

Node i selects the channel j with the largest $\phi_{(i,j)}$ among available channels for the data-packet forwarding.

3. Simulation Evaluation

We evaluate our proposal for clarifying the advantages and properties of our proposal. In this evaluation, the observable information for each node is uncertain (Section 3.1). In Section 3.2, we first evaluate the performance of our proposal in the case where there are nodes with unreliable information for showing that our proposal can overcome the problem of information uncertainty. We then investigate influences of parameters of our proposal in Section 3.3, for clarifying the properties of our proposal.

We use an event-driven packet-level simulator (developed by us) running in Visual C++ on a 64-bit PC with a 2.70-GHz Intel Xeon CPU and 64.0 GB of memory. Nodes are not synchronized in the simulator.

3.1. Simulation Settings

We use the network including 100 nodes (96 sensor nodes and 4 sink nodes). The sensor nodes are deployed randomly in a 550 m $\times$ 550 m field, and the sink nodes are deployed at (137.5 m, 137.5 m), (137.5 m, 412.5 m), (412.5 m, 137.5 m), and (412.5 m, 412.5 m).

Nodes select a channel for data-packet forwarding among 5 channels ($M = 5$). The set $\boldsymbol{c}_i(t)$ of observable channels for node i at time t includes the channel $c_i^{use}(t)$ that node i uses for data-packet forwarding at time t and a fixed set $\boldsymbol{c}'_i$ of observable channels of node i, that is, $\boldsymbol{c}_i(t) = \{c_i^{use}(t)\} \cup \boldsymbol{c}'_i$. Among available channels, one is selected randomly per node as a fixed set $\boldsymbol{c}'_i$ of observable channels of each node i. That is, each node observes at most two channels (observable information for nodes is incomplete). For simplicity and to clarify the advantages and properties of our proposed mechanism, we assume that there is not communication delay in sharing individual information between neighboring nodes.

We artificially define the channel states at each node by setting the probability that channels are observed to be busy. At the beginning of the simulation, the probabilities that channels $\{1, 2, 3, 4, 5\}$ are busy in the channel observation phase of each node are set to $\{0.01, 0.02, 0.03, 0.04, 0.05\}$, respectively. That is, channel 1 has the best quality and channel 5 has the worst. At $10,000$ s after the simulation starts, the busy rate of channel 1 increases to 0.04 in nodes included in the bottom half of the network (observable information for nodes is dynamic). Moreover, at the same time, the reliability of observed information decreases in randomly-selected q nodes included in the bottom half of the network (observable information for nodes is vague). In this evaluation, we set the observable information v in these nodes with unreliable information to a random value. We evaluate changes in the selected channels and performances in nodes included in the bottom half of the network after these state changes.

TABLE 1. NETWORK SETTINGS

Parameter	Value
Data-packet genration rate	0.005 packet/s
Buffur size	1 packet
Communication range	100 m
Carrier sense range	100 m
Transmission speed	100 kbps
Back-off time	$10^{-4} \times$rand(2^p)
p	3∼5
Maximum of back-offs	5

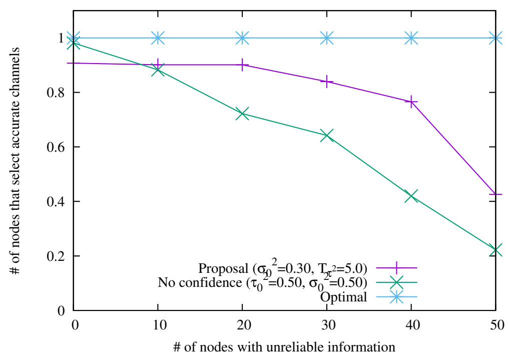


Figure 2. The number of nodes that select accurate channels

For comparison, we adopt channel selection based on collective decision-making with no information confidence (the no-confidence CSM), in which the weights of individual information and social information are fixed (i.e., the variances τ^2 and σ^2 are set to constant values). Moreover, we also adopt the optimal CSM in which each node selects the channel with the highest quality.

In our proposal, each node calculates individual and social information, integrates them, and selects a channel for data-packet forwarding at interval Δt. The interval Δt_{obs} is set to 1.0 s and the time slot Δt is set to 10 s.

We conduct simulation experiments in an environment assuming wireless sensor networks. Nodes forward data packets based on potential-based routing [8]. In the MAC layer, we use intermittent receiver-driven data transmission [9], which is an asynchronous receiver-driven data transmission protocol. As the physical layer model, we use a disk model in which colliding data packets are dropped. The other settings are summarized in Table 1. The results shown below are the averages of 3 simulation runs for different parameter settings.

3.2. Performance Evaluation

For demonstrating that our proposal is advantageous for information uncertainty, we first compare our proposal with the no-confidence CSM and the optimal CSM in the case where there are nodes with unreliable information. In our proposal, the variance σ_0^2 is set to 0.30 and the threshold T_{τ^2} is set to 5.0. In the no-confidence CSM, variances τ_0^2 and σ_0^2 for individual and social information are set to 0.50.

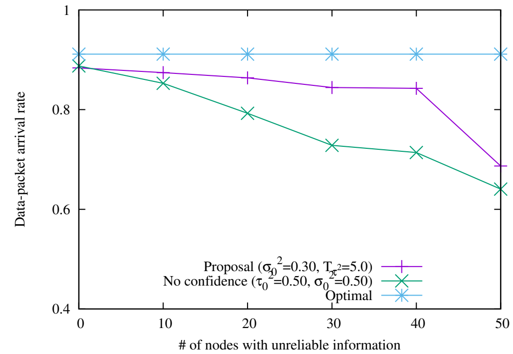
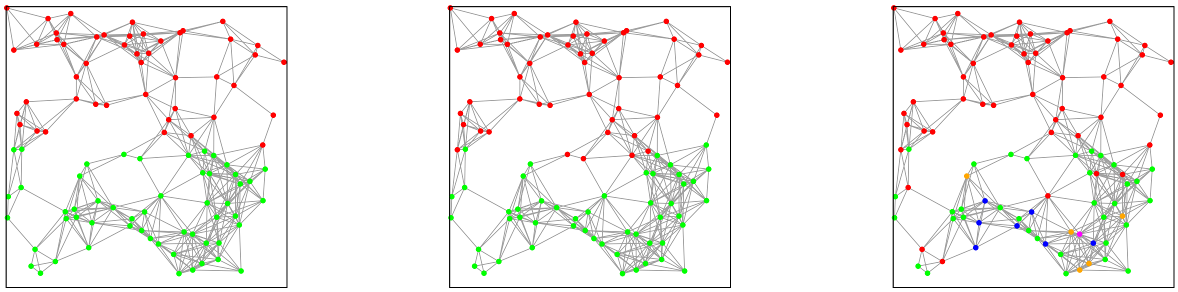


Figure 3. The data-packet arrival rate

Figure 2 shows that the ratio of nodes that select the accurate channel (i.e., channel 2, which is one with the highest quality) against the number of nodes with unreliable information. Figure 3 shows that the data-packet arrival rate against the number of nodes with unreliable information.

From Figure 2, with the no-confidence CSM, as the number of nodes with unreliable information increases, the ratio of nodes that select the accurate channel decreases. This means that more nodes select low-quality channels with a larger number of nodes with unreliable information. With the no-confidence CSM, nodes integrate individual information and social information not considering their confidence, whereby some nodes follow other nodes with unreliable information. This is the cause of the decrease in the ratio of nodes that select the accurate channel. When nodes select wrong channels, the number of the data-packet collisions becomes larger. This leads to low data-packet arrival rates with the no-confidence CSM as shown in Figure 3.

On the contrary, with our proposal, the ratio of nodes that select the accurate channel is higher than that with the no-confidence CSM when the number of nodes with unreliable information is $10 \sim 50$. Even when the number of nodes with unreliable information is 40, the ratio of nodes select the accurate channel is above 0.7. With our proposal, the uncertainty of the observable information is quantified as the variance τ^2 of the individual information. Variances of individual information in nodes with unreliable nodes are larger than those in nodes with reliable information, whereby the importance of individual information of nodes with reliable information is relatively large. Therefore, most nodes attempt to follow other nodes with reliable information. Figure 4 shows the state of channel-selection in the network in the case where the number of nodes with unreliable information is 20. This figure indicates that most nodes select the accurate channel with our proposal. Because the number of data-packet collisions with high-quality channels is lower, the data-packet arrival rate is higher with our proposal as shown in Figure 3. When there is no node with unreliable information, the ratio of nodes selected the accurate channel is lower with our proposal than that with the no-confidence CSM. This is because, with our proposal, some nodes near the boundary may follow high-confidence nodes



(a) Optimal (b) Our proposal (c) No confidence

Figure 4. Channel-selection in the network ($q = 20$)

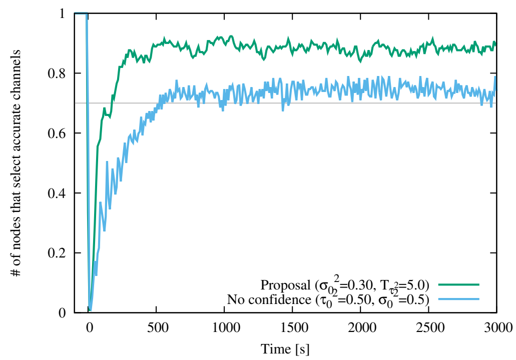


Figure 5. Changes in the ratio of nodes that select the accurate channel

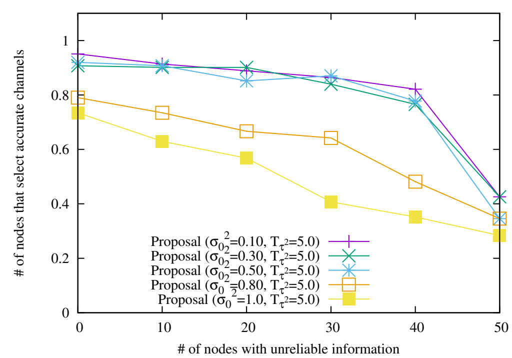


Figure 6. The ratio of nodes that select the accurate channel ($T_{\tau^2} = 5.0$)

with different accurate channels. However, most nodes select the accurate channel, whereby such incorrect decisions have little effect on the performance (the data-packet arrival rate is approximately equal to that with the no-confidence CSM as shown in Figure 3).

Figure 5 shows the changes in the ratio of nodes that select the accurate channel. This figure also indicate that the ratio of nodes that select the accurate channel with our proposal is higher than that with the no-confidence CSM. Moreover, the adaptation speed of channel-selection with our proposal is higher than that with the no-confidence mechanism. Figure 5 indicates that it takes about 200 s for the ratio of nodes that select the accurate channel to become larger than 0.7. In contrast, with the no-confidence channel-selection mechanism, it takes about 500 s. The faster speed of the adaptation to environmental changes of our proposal also contribute to its higher data-packet arrival rate.

Consequently, our proposal can improve the data-arrival rate while retaining the high adaptability to environmental changes although information of nodes is uncertain.

3.3. Influences of Parameters

We next investigate the influences of parameters in our proposal for clarifying the properties of our proposal.

Firstly, we investigate the influences of the variance σ_0^2 of social information. We change σ_0^2 within $0.10 \sim 1.0$

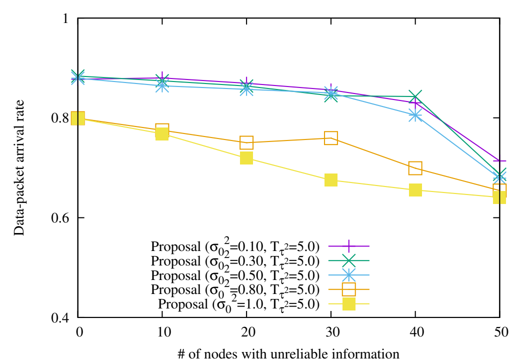


Figure 7. The data-packet arrival rate ($T_{\tau^2} = 5.0$)

while setting T_{τ^2} to 5.0. Figures 6 and 7 show the ratio of nodes that select the accurate channel and the data-packet arrival rate for different variances σ_0^2. From Figures 6 and 7, with a higher σ_0^2 (in this experiments, $\sigma_0^2 = 0.80$ and 1.0), the ratio of nodes that select accurate channel is lower than the case with a lower σ_0^2. When σ_0^2 is high, the weight of social information is relatively lower than that of individual information. This leads nodes to make a decision according individual information regardless of its confidence. As a result, some nodes select wrong channels in accordance with their unreliable information even when there are nodes with

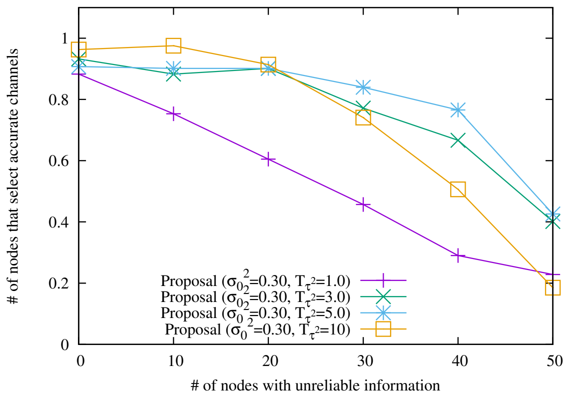


Figure 8. The ratio of nodes that select the accurate channel ($\sigma_0^2 = 0.30$)

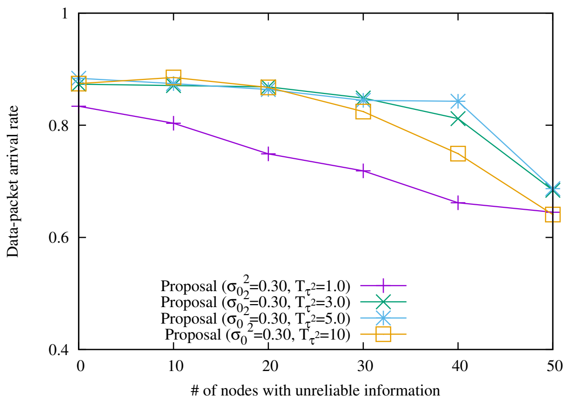


Figure 9. The data-packet arrival rate ($\sigma_0^2 = 0.30$)

reliable information near them. Therefore, too large σ_0^2 is not appropriate for our proposal.

Nextly, we investigate the influences of the threshold T_{τ^2} for calculating social information. For that purpose, we change T_{τ^2} within $1.0 \sim 10$ while setting σ_0^2 to 0.30. Figures 8 and 9 show the ratio of nodes that select the accurate channel and the data-packet arrival rate for different thresholds T_{τ^2}. Figures 8 and 9 indicate that the ratio of nodes that select the accurate channel is lower with a lower T_{τ^2} (in this experiments, $T_{\tau^2} = 1.0$). With a too low T_{τ^2}, individual information obtained from almost of all neighboring nodes is considered as being unreliable when calculating social information by (5). That is, most nodes make decisions only with their own information. As a result, nodes that select wrong channels increase, which lowers the data-packet arrival rate in the network. Moreover, Figures 8 and 9 indicate that the ratio of nodes that select the accurate channel decreases rapidly with a higher T_{τ^2} (in this experiments, $T_{\tau^2} = 10$), when the number of nodes with unreliable information increases. This is because with a too high T_{τ^2}, individual information obtained from almost all neighboring nodes is considered as being reliable when calculating social information. That is, most nodes attempt to follow their neighbors' decisions regardless of the confidence of their information. As a result, the accuracy of the decision-making decreases, thereby lowering the performance of the system. In conclusion, parameter T_{τ^2} needs to be set properly.

4. Conclusion

For overcoming the problem of information uncertainty, we propose a channel-selection mechanism according to information confidence inspired by the concept of flexible leadership of decision making in human groups. Through simulation experiments, we show that, by introducing our proposal, the decision accuracy and speed are improved while retaining the high adaptability. Moreover, we demonstrate the influences of parameters to the performance of our proposal.

In future work, we will consider the scalability and robustness of our proposal. Moreover, we will consider the scheme for determining the confidence of each node's information considering the outcome of the previous decision. For realizing such mechanism, we will introduce the learning mechanism of feedbacks in human's brain.

Acknowledgments

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References

[1] F. Dressler, *Self-organization in sensor and actor networks*. USA: Wiley, Jan. 2008.

[2] M. Prokopenko, *Guided Self-organization: Inception*. Berlin: Springer, Jan. 2014.

[3] A. K. Seth, "The cybernetic Bayesian brain – from interoceptive inference to sensorimotor contingencies," *Open MIND*, pp. 1–24, 2014.

[4] L. Conradt, "Models in animal collective decision-making: information uncertainty and conflicting preferences," *Interface Focus*, pp. 1–5, Dec. 2011.

[5] N. Kuze, D. Kominami, K. Kashima, T. Hashimoto, and M. Murata, "Self-organizing control mechanism according to information confidence inspired by decision-making in human groups," submitted to *ACM Transactions on Autonomous and Adaptive Systems*, Mar. 2018.

[6] R. H. J. M. Kurvers, M. Wolf, M. Naguib, and J. Krause, "Self-organized flexible leadership promotes collective intelligence in human groups," *Royal Society Open Science*, vol. 2, no. 12, Dec. 2015.

[7] S. A. Park, S. Goïame, D. A. O'Connor, and J.-C. Dreher, "Integration of individual and social information for decision-making in groups of different sizes," *PLoS Biology*, vol. 15, no. 6, pp. 1–28, Jun. 2017.

[8] N. Kuze, D. Kominami, K. Kashima, T. Hashimoto, and M. Murata, "Controlling large-scale self-organized networks with lightweight cost for fast adaptation to changing environments," *ACM Transactions on Autonomous and Adaptive Systems*, vol. 11, no. 2, pp. 9:1–9:25, Jun. 2016.

[9] D. Kominami, M. Sugano, M. Murata, and T. Hatauchi, "Controlled and self-organized routing for large-scale wireless sensor networks," *ACM Transactions on Sensor Networks*, vol. 10, no. 1, pp. 13:1–13:27, Nov. 2013.