International Journal of Innovative
Computing, Information and Control
Volume **10**, Number **1**, February **2014**

ICIC International ©2014 ISSN 1349-4198
pp. 373–387

ADAPTIVE STRATEGIES: A NOVEL GAME-THEORETIC ANALYSIS FOR AUTONOMOUS DISTRIBUTED SYSTEMS IN DYNAMIC ENVIRONMENTS

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Received January 2013; revised May 2013

Abstract. *We propose a new concept of an adaptive strategy, and we consider its robustness against other strategies. On average, the adaptive strategy achieves a higher payoff than other strategies. The strength of a strategy is defined as an adaptive measure calculated on the basis of a payoff obtained through interactions among agents. An agent interacts with other agents by selecting various strategies in computer networks. For the adaptive strategy, we give a formal definition of the adaptive measure of how well it behaves against other strategies. In order to demonstrate a performance of the adaptive strategy, we present a calculation example of the adaptive measure for the iterated prisoner's dilemma with three simple strategies. In the example, Trigger strategy is found to be the best strategy when we evaluate it by the adaptive measure, even if All-D (always defect) strategy achieves the highest expected payoff. Furthermore, we investigate the adaptive strategies for a self-repairing network consisting of agents with spatial strategies. According to simulations, under some conditions, the strategies obtaining the highest adaptive measures do not correspond to those with the highest averaged resources. The significance of the adaptive strategies is considered with a statistical analysis. The adaptive measure enables us to evaluate the behaviors of the adaptive strategies against those of other strategies. In addition, we discuss some open problems for polishing a notion of the adaptive strategies.*

Keywords: Game theory, Adaptive strategy, Prisoner's dilemma, Autonomous distributed systems, Self-repairing network

1. Introduction.

Autonomous distributed systems need to adapt to dynamic environments, that is, environments that change spatiotemporally. In autonomous distributed systems, the agents interact with the connected neighborhood. The conditions of the neighborhood vary according to changes of environmental conditions. The agents need to proceed with their own assigned tasks to earn their profit in the environment. Therefore, they need to follow and adapt to changes in the environment to obtain their profits as much as possible.

An example of an autonomous distributed system is a self-repairing network [7,9,10,14]. A self-repairing network is a model in which the agents mutually repair each other. It consists of agents connected to neighbor agents with a certain network structure such as a square lattice network. The model assumes that the agents can be abnormal by infection of malicious programs or a spontaneous failure. Since abnormal agents would be harmful for normal agents, the agents need to control their repair rate to adapt to the changing environment. In this situation, the altruistic behavior of repairing other agents is needed to prevent the network from contamination, because abnormal agents could infect normal agents, thereby contaminating them. The behavior of the abnormal agents would be regarded as different strategies, as compared with those of the normal agents. The normal agents repair other agents, and they control their repair rate to prevent contamination of the network.

Another example involves routing problems in computer networks. Routing problems have been studied using a game theoretic approach [11,17] to prevent collision of the data transmission in the networks. In routing problems, the behavior of the agents [13] and a cooperation mechanism [16] are studied. Selfish agents aim to transmit their data to specific destinations. However, the capacity of the links is limited. The major issue in routing problems is to determine how the agents assign their traffic for each link with the smallest possible latency. Moreover, network traffic will change dynamically according to the demand of the agents. Therefore, devising strategies for sending data with minimum latency is a crucial issue.

Several concepts for evaluating strategies have been investigated. In the autonomous distributed systems, to model and evaluate behavior of the agents is a crucial issue. Evolutionary game theory has been used for understanding the evolution of biological systems [18,20]. The game theoretic approach for investigating biological systems is based on the notion of an evolutionarily stable strategy (ESS), which prevents an intrusion from a small number of mutants in the population. Such strategies can survive when their fitness exceeds that of intruders. An extension of the ESS for stochastic processes has also been investigated for random environments [5].

In game theory, fault-tolerant strategies are investigated in the iterated prisoner's dilemma (IPD) [15]. The simple tit-for-tat (TFT) strategy exhibited excellent performance in a round-robin tournament of the IPD [1]. The TFT strategy gained higher payoffs against cooperative strategies than against defective strategies. However, it is vulnerable to errors such as misinterpretation of the actions of opponents. The study [15] defined fault-tolerant strategies under error conditions.

In this paper, an adaptive strategy [19] is proposed, and its robustness in autonomous distributed systems is considered. The agents meet other agents which implement various strategies in the environments. The adaptive strategy earns a higher payoff than other strategies and cooperates with them. The definition does not require that the strategies always obtain the highest payoffs. The optimal strategies (i.e., those earning the highest payoff) would differ according to changes in the environmental conditions. We consider the self-repairing network as an example. No-reaction (not repair) strategies would emerge and lead the network to absorbed states in which all the agents are abnormal. It would be difficult for abnormal agents to maintain a high level of resources owing to their state. The repairing (repair other agents) strategies could avoid this situation by mutual repairing; however, the agents consume their resources by repairing other agents. Nonetheless, the agents achieve a higher payoff than that achieved in a situation involving selfish agents. Therefore, we need to consider adaptive strategies obtaining a high payoff against other strategies in that environments. The scope of this paper is confined to the situation in which two strategies meet in the game under static conditions.

The proposed concept of adaptive strategies differs from the aforementioned ESS and fault-tolerant strategies; it considers how well adaptive strategies behave for other strategies. The performance of adaptive strategies is evaluated as an adaptive measure. The adaptive measure of the adaptive strategy is calculated on the basis of payoffs obtained through interactions among the agents. We propose a formula for the adaptive measure that includes factors of cooperation and self-tolerance. The adaptive measure of the strategy will increase when it behaves cooperatively with itself and others.

The proposed measure enables us to design an adaptive strategy and to evaluate its effectiveness. For autonomous distributed systems, we need to design and evaluate the strategy quantitatively in order to construct adaptive systems. Our measure is helpful for evaluating how well the strategy cooperates with not only itself but also other strategies.

The remain of this paper organizes as follows. In Section 2, we give a formal definition of adaptive strategies, and we present a calculation example of the iterated prisoner's dilemma with three simple strategies. In Section 3, we introduce and define the self-repairing network for simulations. In Section 4, we apply and evaluate the proposed measure for the self-repairing network. In Section 5, we discuss the significance of the adaptive strategies on the basis of the simulation results, and we also propose several open problems for adaptive strategies. Finally, in Section 6, we state our conclusions regarding the effectiveness of the adaptive strategies.

2. **Adaptive Strategy.** In this section, the concept of adaptive strategies is introduced, and a formal definition is provided. We introduce the concept of an adaptive strategy earns the high payoff, on average, against other strategies. This means that the adaptive strategy earning the high payoff behaves well against various opponents. Furthermore, the concept of an adaptive strategy involves the essence of adaptive systems.

The construction of an autonomous distributed system by the game-theoretic approach needs to incorporate design strategies for the agents, because selfish behavior would lead the systems to absorbed states [3,11,17]. Thus, adaptive systems would not achieve the desired performance. Designing a cooperation mechanism between agents is a crucial issue because the agents behave selfishly [4,9,14,16]. The cooperation mechanism plays an important role in autonomous distributed systems.

Pioneering work for cooperative strategies in the IPD [4] had been carried out by Axelrod [1]. He held a round-robin tournament of two-player IPD. For the tournament, he gathered the strategies from participants and organized games among them. Finally, the winner of the round-robin tournament was chosen from the participants who earned the highest score.

According to the report, he concluded that TFT strategy was the best approach for winning the tournament. TFT strategy is a simple strategy. In the first round, the strategy involves playing cooperatively. After the first round, a TFT strategy follows the action of the opponent in the previous round. Therefore, players can earn a higher payoff than if they choose defection if the opponents determine the next move cooperatively. Axelrod concluded that TFT strategy was successful against various strategies in the IPD round-robin tournament.

In computer networks, many types of strategies are available to agents. Cooperative strategies such as TFT would work well against various strategies, even if they interact with egoistic strategies. Obviously, the egoistic strategies would exist and prevail. The agents have opportunities to interact with each other because they are connected by the network structure. They could increase their payoff through mutual cooperation. Selfish agents would decrease their payoff by mutual defection. However, selfish agents can exploit the payoff of cooperating opponents. An altruistic strategy would not exhibit the highest performance because of this exploitation by selfish agents. However, adaptive strategies would perform well under various situations.

In order to construct an autonomous distributed system, we need to define the adaptive strategies and evaluate how well these strategies behave. For dynamic environments, systems need to be adaptable. In computer networks, threat strategies would possibly emerge and intrude into the system. In this situation, the agents need to cooperate with each other to prevent intrusions. However, the degree of altruistic behavior is one of several parameters because excessive cooperation among agents decreases the performance of the system [2]. Therefore, a measurement of the adaptive strategies is needed for designing and evaluating the system.

From the above reviews, the concept of an adaptive strategies involves two fundamental factors: (a) cooperation and (b) self-tolerance. Cooperation means that the strategies need to behave cooperatively to maintain their performance against the opponents because the agents would encounter all kinds of strategies in a computer network. Self-tolerance means that the agents need to cooperate with their neighboring connected agents because if they defect from others who have the same strategies, they would lose future opportunities to get a higher payoff. These two fundamental factors require agents to cooperate not only with themselves but also with other agents.

The measurement of an adaptive strategy is defined by payoffs and strategies. Let S denote a set of strategies. Let N denote the cardinality of the strategy set S. Let i, j, and k denote natural numbers used for numbering the strategies in the strategy set. Strategy s_i is expressed as one strategy in the set S numbered as i. Let $E_p[s_i|s_j]$ denote the expected payoff of strategy s_i against s_j. Let $E_m[s_i]$ be the expected payoff of the strategy s_i for all strategies.

We call an adaptive measure $E[s_i]$ of a strategy s_i its strength. The adaptive measure is represented based on the payoffs through the interactions in games as follows:

$$E[s_i] = \frac{1}{NM} \sum_{s_j \in S} E_p[s_i|s_j] E_m[s_j] \tag{1}$$

$E_m[s_j]$ is expressed as follows:

$$E_m[s_j] = \frac{1}{NM} \sum_{s_k \in S} E_p[s_j|s_k] \tag{2}$$

The symbol M represents the maximum total payoff in the payoff matrix of the game. Equation (2) represents the averaged performance of strategy s_j for all strategies. The adaptive measure in Equation (1) is expressed as the product of $E_p[s_i|s_j]$ and $E_m[s_j]$ to evaluate whether strategy s_i achieves the higher payoff against strategy s_j even if s_j achieves a high payoff for other strategies. The adaptive measure will decrease when strategy s_i achieves the smaller payoff and also even if strategy s_j achieves the higher averaged payoff. In contrast, the adaptive measure will increase when strategy s_i gets a larger payoff and strategy s_j obtains the higher averaged payoff. The range of the measure can be normalized from zero to one. The strategy is adaptive if the measure is close to one, and it is not adaptive if the measure is close to zero. The adaptiveness of the strategies can be evaluated by comparing with the adaptive measures.

We present a calculation example of the adaptive measures of the adaptive strategies in the iterated prisoner's dilemma (IPD). In the following example, we show the calculation example of the adaptive strategy analysis using typical values. This example uses simple three strategies: All-C (always cooperate), All-D (alway defect) and Trigger (it cooperates until an opponent defects in a previous round, otherwise defects). We demonstrate that Trigger strategy obtains the highest adaptive value and gets the high payoff against other strategies in the given setting.

The IPD is a temporal extension of the prisoner's dilemma. The prisoner's dilemma [1] is a one-shot game whereas the IPD is a repeated game. We consider a two-player game in the infinite IPD. The players determine their actions of cooperation or defection simultaneously without prior consultation before the game. The payoff for each player is determined by combinations of moves among the players. Each symbolic value in the table satisfies the conditions $T > R > P > S$ and $2R > T + S$.

In the first example, we assume a discount rate of the payoff for every round of $w = 0.995$. The discount rate can be used for calculating the discounted payoff regarded as the future payoff. The expected payoffs of the infinite IPD for the three strategies can be calculated theoretically [1]. The theoretical results shown in Table 2 are calculated from the payoff matrix shown in Table 1.

TABLE 1. Payoff matrix in the prisoner's dilemma from the proponent's point of view

		Player 2	
		C	D
Player 1	C	$R = 3$	$S = 0$
	D	$T = 5$	$P = 1$

TABLE 2. Expected payoff in the infinite IPD from the proponent's point of view

		Opponent		
		All-C	All-D	Trigger
Proponent	All-C	$\frac{3}{1-w}$	0	$\frac{3}{1-w}$
	All-D	$\frac{5}{1-w}$	$\frac{1}{1-w}$	$5 + \frac{w}{1-w}$
	Trigger	$\frac{3}{1-w}$	$\frac{w}{1-w}$	$\frac{3}{1-w}$

TABLE 3. Expected payoff in the infinite IPD from the proponent's point of view where $w = 0.995$

		Opponent		
		All-C	All-D	Trigger
Proponent	All-C	600	0	600
	All-D	1000	200	204
	Trigger	600	199	600

Typical numerical results are shown in Table 3. We calculate the measures of the adaptive strategies from Table 3. The $E_m[s_j]$ values are obtained as follows:

$$E_m[\text{All-C}] = \frac{600 + 600 + 0}{3 \cdot 1000} = 0.4 \quad (3)$$

$$E_m[\text{All-D}] = \frac{200 + 1000 + 204}{3 \cdot 1000} = 0.468 \quad (4)$$

$$E_m[\text{Trigger}] = \frac{600 + 600 + 199}{3 \cdot 1000} = 0.466 \quad (5)$$

Therefore, we obtained the adaptive measures by calculating with above values.

$$\begin{aligned} E[\text{All-C}] &= \frac{600 \cdot 0.4 + 600 \cdot 0.466 + 0 \cdot 0.468}{3 \cdot 1000} \\ &= 0.173 \end{aligned} \tag{6}$$

$$\begin{aligned} E[\text{All-D}] &= \frac{200 \cdot 0.468 + 204 \cdot 0.466 + 1000 \cdot 0.4}{3 \cdot 1000} \\ &= 0.196 \end{aligned} \tag{7}$$

$$\begin{aligned} E[\text{Trigger}] &= \frac{600 \cdot 0.466 + 600 \cdot 0.4 + 199 \cdot 0.468}{3 \cdot 1000} \\ &= 0.204 \end{aligned} \tag{8}$$

According to Table 3, the All-D strategy earns the highest expected payoff among the three strategies. The measures of All-D and Trigger are very close. However, the adaptive measure for Trigger is a little larger than that for All-D. The calculation of the adaptive measures shows that the Trigger strategy behaves well against itself and the other two strategies. This example demonstrates that the strategy earning the high payoff does not correspond to the one with the highest adaptive measures.

3. **Self-Repairing Network.** In this section, the self-repairing network is defined to demonstrate another example of adaptive strategies. The self-repairing network is a mutual repairing model [7,9,14] comprising agents with spatial strategies [8,10] for determining their actions. The self-repairing network is suitable to demonstrate in oder to consider the adaptive strategies as an example since the conditions of the network change by mutual repairing and spontaneous failure. We measure the performance of each spatial strategy from the viewpoint of adaptive strategies.

We assume that self-repairing takes place on a square lattice network. Each agent is placed at each cell in an $L \times L$ two-dimensional network (Figure 1). Periodic boundary conditions are imposed on the network. Each agent interacts with eight others in its neighborhood.

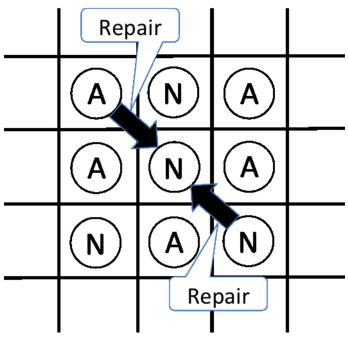
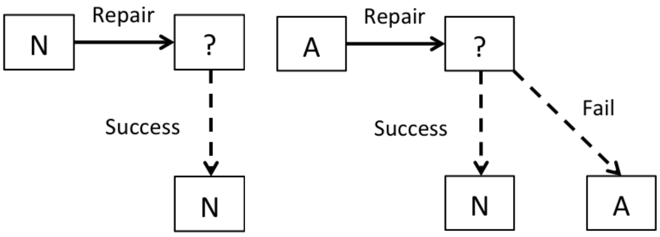


FIGURE 1. Spatial arrangement of agents in self-repairing network

Each agent is in either a normal state or an abnormal state. A normal state represents a situation in which the agent works well, whereas an abnormal one represents a condition of being infected by malicious programs. The agent is repaired from its neighborhood (Figure 2). The repairing occurs between two agents. All agents simultaneously repair other agents on the basis of their own decisions.

The agents have their own spatial strategies to determine their next actions. The strategies are determined through decisions based on the spatial configuration of the neighborhood of the agents. In a previous study [8], several types of strategies have



(a) (b)

FIGURE 2. Schematic illustration of repairing by normal and abnormal agents. (a) Repairing by normal agents. (b) Repairing by abnormal agents. The question mark represents the state of the agent is unknown. The repair success rates are different according to the states of the agents.

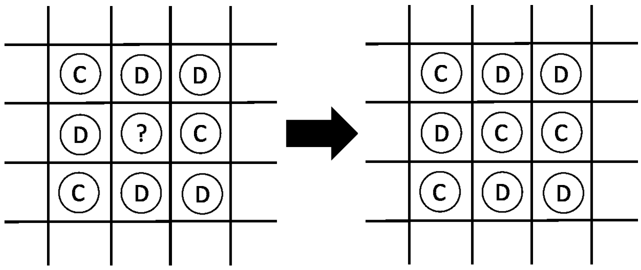


FIGURE 3. Example of action decision of kC strategy where the threshold $k = 4$ (4C strategy)

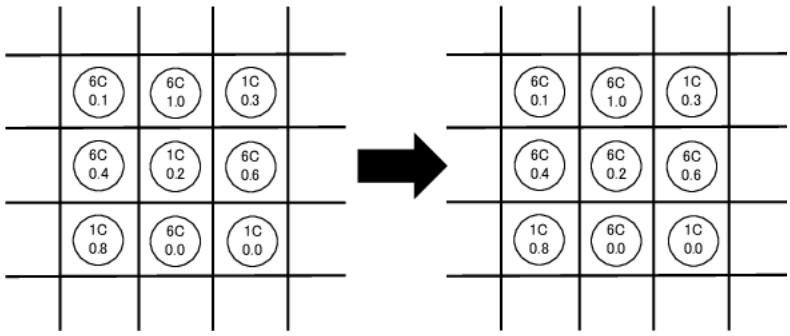


FIGURE 4. Strategy update. The upper and lower symbols represent strategies and resources. The central agent chooses the 6C strategy after updating.

been demonstrated and evaluated on the basis of a round-robin tournament of the spatial prisoner's dilemma [4,8].

In spatial strategies, the specific examples are kD and kC strategies [8]. The kD strategy chooses defection if the number of defectors in the neighborhood is larger than or equal to the threshold k; otherwise, it chooses cooperation. In contrast, the kC strategy selects cooperation if the number of defectors in the neighborhood is larger than or equal to the threshold k; otherwise, it selects defection. The number of defective neighborhoods depends on the arrangement of the agents in the network. In this paper, we apply the kC strategy to all agents. The 0C ($k = 0$) and the 8C ($k = 8$) strategies correspond to All-C and All-D strategies, respectively, when the number of neighborhoods is restricted to only one agent and its neighbors.

Figure 3 shows an example of the action decision of the kC strategy. In Figure 3, the centered agent finally chooses cooperation when it has the 4C strategy because the number of defections exceeds the threshold $k = 4$. The kC strategy is suitable for self-repairing networks because it selects cooperation for repairing other agents when neighbors do not do in the previous step.

The agents are assigned the available resources for repairing and their tasks at every step. The available resources of the agents are temporal resource for computation. They determine to consume/save it based on their actions. Normal agents have maximum resources of $R_{\max}$, whereas abnormal agents have no resource (empty resource). Resources for abnormal agents are always evaluated as empty. This means that the abnormal agents do not work well because of their contaminated state. The normal agents recovered from abnormal state in the previous step also have maximum resources of $R_{\max}$. When agents repair other agents once, they consume R_r of their resources. In our model, the agents consume $8R_r$ of their resources if they repair all neighbors. They assign the remaining resources for their task after repairing. The remaining resources are used for calculating their scores. The score is used for evaluating the success of repairing and for performing a strategy update.

The agents update their strategies at every step. Figure 4 shows an example of the strategy update. The agents switch from their strategies to the strategies that earn the highest score in the neighborhood. This update allows the agents to select the best strategies for adapting to the condition of the network. In Figure 4, the centered agent updates its strategy to the 8C strategy, which achieves the highest payoff score in the neighborhood. The agents get opportunities to earn a higher score because they are allowed to update their strategies to those that are favored in the environment. A strategy update error occurs when the agents update their strategies. The agents adopt other strategies with a strategy update error rate μ. This mechanism contributes to preventing local minima of the network.

4. **Simulations.** In this section, we present simulations of the self-repairing network, and we calculate the adaptive measures for the strategies. We consider the relationship between adaptive measures and total resources of the strategies from the simulation results. We conduct simulations of a round-robin tournament of spatial strategies. The measures of the adaptive strategies are calculated after the round-robin tournament. The simulation parameters are listed in Table 4. In Table 4, the number of the trial for each simulation condition is sufficient for the statistical analysis.

In the simulations, two strategies constitute one game in the self-repairing network. One round of the tournament consists of a number of games, T_a, shown in Table 4. All the strategies play the game with all other strategies, including themselves. After the round-robin tournament, we calculate the total resources of each strategy over every time, and then, we calculate the adaptive measures for each strategy.

Figure 5 shows the averaged resources when the failure rate is changed. The averaged resources are calculated from all of the results of the round-robin tournament for each failure rate. The averaged resources decrease as the failure rates increase. The maximum averaged resources are obtained when the failure rate is 0.0. The minimum averaged resources are obtained when the failure rate is 0.1. Figure 5 shows that averaged resources converge with increasing failure rate. From these results, we consider the adaptive strategies affected by the failure rate under the conditions $\lambda = 0.01$, because in this case, the agents keep relatively higher averaged resources.

Table 5 lists the total resources of the game for two strategies (Table 5(a)) and their averaged total resources for all strategies (Table 5(b)). The 5C strategy earns the highest

TABLE 4. Parameters for agent simulations

Parameter	Name	Value
T_a	Step	1000
N_t	Number of trial	35
$L \times L$	Number of total agents	2500
$N(0)$	Probability of normal agents at initial step	0.2
C(0)	Agents choosing repair action at initial step	0.5
α	Repair success rate by normal agents	1.0
β	Repair success rate by abnormal agents	0.1
$R_{\max}$	Maximum resources	1.0
R_r	Repair resources	0.1
λ	Failure rate	0.01-0.10
S	Strategy update cycle	1
μ	Strategy update error rate	0.001

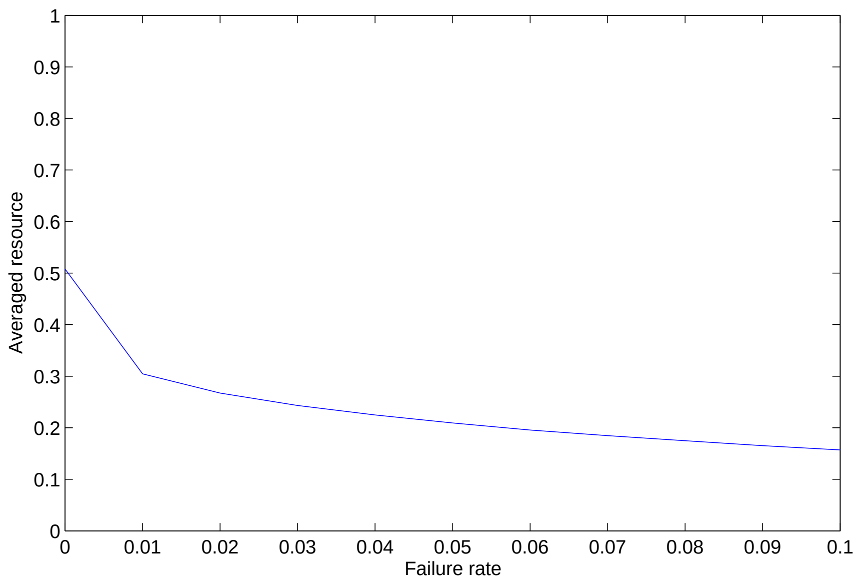


FIGURE 5. Averaged resource for failure rates

averaged total resource value of 841.7. The second highest value 778.7 is obtained by the 6C strategy. The 5C strategy reaches a higher resource when the generosity of the opponents is not more than $k = 5$. It reaches a lower resource when the generosity exceeds $k = 5$ of the opponents. In contrast, the 6C strategy yields smaller averaged resources than the 5C strategy when the threshold is not more than $k = 6$. However, it also yields higher averaged resources for the 7C and 8C strategies. For these two adversarial strategies, the 5C strategy does not have sufficient resources. However, the 6C strategy keeps higher resources than the 5C strategy. As shown in Table 5(b), the standard deviations of averaged total resources also show that its value of the 6C strategy is smaller than one of 5C strategy.

Table 6 lists the adaptive measures of the strategies. The values in Table 6 are calculated using the results of the round-robin tournament. The highest value of the adaptive measures is for the 6C strategy. The adaptive measure of the 6C strategy is 0.0491, which

Table 5. Total resources of the round-robin tournament where the failure rate is $\lambda = 0.01$

(a) The round-robin tournament result. The rows and columns represent the proponents and opponents, respectively. The total resources of each cell represent the values from the proponent's point of view.

	0C	1C	2C	3C	4C	5C	6C	7C	8C
0C	450.6	30.7	4.6	1.3	0.6	0.4	0.4	0.6	0.8
1C	426.9	458.9	6.5	1.4	0.7	0.4	0.4	0.7	0.8
2C	509.4	505.8	513.5	4.6	0.8	0.5	0.5	0.8	1.0
3C	709.9	709.3	705.9	715.7	4.4	1.0	1.0	1.8	2.0
4C	1051.0	1050.5	1055.9	1046.8	1029.7	5.2	5.6	7.7	10.2
5C	1249.0	1252.3	1250.3	1237.9	1224.5	1161.3	41.2	78.1	80.6
6C	972.3	982.4	977.9	954.6	932.2	886.6	762.3	273.2	267.1
7C	690.5	699.0	682.9	668.0	629.6	585.9	326.2	228.5	120.8
8C	643.0	637.5	632.6	621.4	566.9	520.1	275.2	73.3	64.4

(b) Total resource of each strategy calculated from Table 5(a)

Strategy	Total resource	S. D.
0C	54.5	140.4
1C	99.6	183.6
2C	170.8	239.6
3C	316.8	351.9
4C	584.7	516.6
5C	841.7	548.8
6C	778.7	279.4
7C	514.6	212.8
8C	448.3	229.7

Table 6. Adaptive measures of the strategies where the failure rate is $\lambda = 0.01$. S. D. (A) and (B) respectively represent standard deviations of adaptive measures and total resources.

Strategy	Adaptive measure	S. D. (A)	Total resource	S. D. (B)
0C	0.0005	4.20×10^{-5}	54.4	140.4
1C	0.0013	1.67×10^{-5}	99.6	183.6
2C	0.0030	6.92×10^{-5}	170.8	239.6
3C	0.0082	2.51×10^{-4}	316.8	351.9
4C	0.0230	4.24×10^{-4}	584.7	516.6
5C	0.0462	8.93×10^{-4}	841.7	548.8
6C	0.0491	1.61×10^{-3}	778.7	279.4
7C	0.0306	1.22×10^{-3}	514.6	212.8
8C	0.0258	6.93×10^{-4}	448.3	229.7

is larger than that for the 5C strategy. The adaptive measure of the 5C strategy is in the second place. In the results of Table 5(b), the 5C strategy achieves the highest averaged total resource in the round-robin tournament. However, the 6C strategy behaves well against other strategies in the games from the viewpoint of adaptive measures. For the

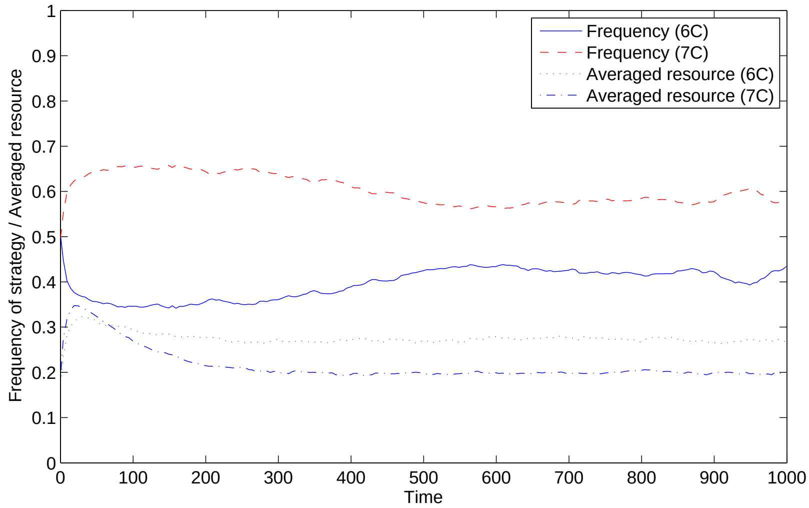


FIGURE 6. Averaged resources and frequency of strategies for the game of 6C vs. 7C

averaged total resource, the standard deviation of the 6C strategy is smaller than the one of the 5C strategy. The 6C strategy achieves the highest adaptive measure among the strategies because it cooperates even if it meets agents choosing strategies such as the 7C and the 8C strategies. The 5C strategy does not cooperate (not repair other agents) against 6, 7, and 8C strategies.

For this case, the significant difference on the adaptive measures between 5C and 6C strategies is evaluated statistically by Welch's t-test with a significance level $p = 0.05$. The result of the t-test shows that the adaptive measures of the two strategies is significantly different. The calculation of the adaptive measure quantifies that the 6C strategy gets the high payoff against other strategies. The evaluation by the adaptive strategy succeeds in quantifying the performance of the 6C strategy.

Figure 6 shows the time development of the averaged resources and frequency of the 6C and 7C strategies; the averaged resource value of the 7C strategy is smaller than that for the 6C strategy. The frequency of the 7C strategy is larger than that of the 6C strategy. Though the frequency of the 6C strategy is smaller than that of the 7C, the agents of the 6C strategy repair other ones and keep the high resource. From this figure, the performance of the 6C strategy against the 7C strategy corresponds to the results in Table 6. The 6C strategy obtains the higher payoff than 7C strategy even the 5C strategy fails to get the high payoff against it.

Table 7 shows the comparisons between averaged total resources and adaptive measures for each failure rate. In almost all cases, the strategies of the highest adaptive measures differ from ones of the highest averaged total resources. We examine the significant difference on the adaptive measures between two strategies by Welch's t-test. These two strategies indicate the highest adaptive measures and the highest total averaged resources, respectively. According to the statistical analysis, the results only show that the difference of the adaptive measures of both strategies are significantly different where failure rates are $\lambda = 0.01, 0.08$. In other cases, the difference of the adaptive measures of both strategies are not significantly different. Namely, the strategies of the highest adaptive measures and the averaged total resource show the same performance from the view point of the adaptive strategy. However, these strategies obtain the high payoff relatively and they minimize their standard deviations to be small.

Table 7. Strategies of highest averaged total resources and adaptive measures of the adaptive strategies for each failure rate

(a) Strategies obtaining the highest resource. S. D. (A) and (B) respectively represent standard deviations of adaptive measures and total resources.

Failure Rate	Strategy	Adaptive measure	S. D. (A)	Total resource	S. D. (B)
0.00	6C	0.1125	3.21×10^{-3}	1339.3	580.8
0.01	5C	0.0462	8.93×10^{-4}	841.7	548.8
0.02	5C	0.0377	8.26×10^{-4}	753.4	488.1
0.03	5C	0.0317	6.56×10^{-4}	687.8	442.9
0.04	5C	0.0273	5.93×10^{-4}	637.2	405.5
0.05	5C	0.0235	4.38×10^{-4}	590.8	374.6
0.06	5C	0.0205	3.83×10^{-4}	552.8	344.6
0.07	5C	0.0183	3.15×10^{-4}	520.9	320.5
0.08	5C	0.0161	3.15×10^{-4}	488.2	297.6
0.09	5C	0.0145	3.01×10^{-4}	462.0	276.9
0.10	5C	0.0130	2.48×10^{-4}	436.9	257.0

(b) Strategies obtaining the highest adaptive measures. S. D. (A) and (B) respectively represent standard deviations of adaptive measures and total resources.

Failure Rate	Strategy	Adaptive measure	S. D. (A)	Total resource	S. D. (B)
0.00	6C	0.1125	3.21×10^{-3}	1339.3	580.8
0.01	6C	0.0491	1.61×10^{-3}	778.7	279.4
0.02	6C	0.0382	1.57×10^{-3}	676.1	210.2
0.03	6C	0.0320	1.29×10^{-3}	615.8	177.2
0.04	5C	0.0273	5.93×10^{-4}	637.2	405.5
0.05	6C	0.0235	6.88×10^{-4}	525.2	133.2
0.06	5C	0.0205	3.83×10^{-4}	552.8	344.6
0.07	5C	0.0183	3.15×10^{-4}	520.9	320.5
0.08	6C	0.0164	4.83×10^{-4}	435.6	91.2
0.09	6C	0.0146	4.46×10^{-4}	410.6	82.0
0.10	6C	0.0131	3.54×10^{-4}	389.1	71.5

5. **Discussion.** In this paper, the concept of an adaptive strategy has been proposed, and examples of its measures also have been presented. The proposed measurement for an adaptive strategy allows us to evaluate how well the strategy behaves cooperatively and earns payoffs against other strategies.

In the example of the iterated prisoner's dilemma (Section 2), Trigger strategy achieves the highest adaptive measure among the strategies, even though the All-C strategy achieves the highest averaged payoff. In the game, mutual cooperation among Trigger and All-C strategies leads to higher payoffs than mutual defection. Furthermore, the behavior of the Trigger strategy differ from that of the All-C strategy when the opponent chooses defection in the previous round. Trigger strategy chooses defection in retaliation. As a result, Trigger strategy prevents exploitation from the All-D strategy. Therefore, it achieves the highest adaptive measure. The proposed measure demonstrates the adaptiveness of Trigger strategy against other strategies.

In the simulations (Section 4), we calculated adaptive measures for the self-repairing network with spatial strategies. The 6C strategy achieves the highest adaptive measures under two different failure rates. However, this is not the strategy with the highest averaged resources. The 6C strategy is more cooperative than the 8C (All-D) strategy because it repairs other agents if the number of defectors is larger than 6. All-D strategy does not contribute to maintaining the network. The 5C strategy achieves the highest averaged resource value in the round-robin tournament. However, the 5C strategy loses resources, as compared with the 6C, the 7C, and the 8C strategies. From these results, we state that adaptive strategies lead to the highest adaptive measures, even though they do not earn the highest payoff. The simulations show that the analysis by the adaptive strategies allows us to find the strategies earning the high payoff in the strategy set.

However, the spatial structure and strategy update contribute to the success of the adaptive strategies in the simulations. Agents switch to new strategies via the strategy update since they connect to each other through the square lattice network. Agents favor the strategies that earn high payoffs in the neighborhood. The network structure supports the clustering of agents with the same strategies. Agents obtain their high payoff by mutual cooperation because cooperation is promoted by the network structure [12,13]. These two factors would contribute to the success of the adaptive strategy against other strategies.

The adaptive strategy analysis can be applied to other autonomous distributed systems in computer networks. The example analysis is shown in Section 4. In the autonomous distributed systems, to design the robust strategies earning the high payoff against other ones is a crucial issue. In computer networks, selfish agents (defective agents) possibly emerge under certain conditions. Selfish behaviors are more rational than altruistic behaviors because egoistic strategies would exploit the payoffs from agents with altruistic behaviors. The proposed measurement of the adaptive strategies can be used to evaluate the robustness of the strategies against unexpected intrusion strategies. In the simulations, the 6C strategy exhibits its robustness against other strategies because it achieves the highest payoffs from its opponents. Therefore, we think that the demonstration of the simulations shows possibility of adaptive strategies as an application to information systems.

For understanding, the analysis of the adaptive strategies would be applicable to other systems, e.g., an immune system [6]. The immune system spatiotemporally changes of internal body on attacks from antigens. The immune system controls the fraction of antibody sufficiently for eradicating antigens. Many kinds of antigens appear and damage to the body. However, the immune system shows adaptation for changes of attacks from antigen and cure it. From game theory point of view, the authors think that the proposed strategy evaluate quantitatively an adaptability of the antibody against various kinds of antigens.

We discuss open problems of the adaptive strategies considered from the results in Section 4. For the first problem, the conditions to which strategies of the highest measures and payoffs correspond are necessary to be considered. In the prisoner's dilemma example and the simulations, several cases do not show correspondence between the strategies of the highest adaptive measures and the highest averaged total resources. In other cases, however, the strategies of both measures correspond. In the example of the prisoner's dilemma, the existence of the adaptive strategies is proved numerically. The simulations statistically show that the difference between the adaptive measures of the strategies is significantly different. We need to investigate the conditions in which this correspondence exists.

The second problem is that the identification ability of the adaptive strategies is necessary to be more improved. Because the evaluations show the correspondence of the adaptive measures even the averaged total resource is different. According to the simulations, some strategies are candidate of the adaptive strategies. The adaptive strategies obtain the high payoff with a small standard deviation as shown in the simulations. For the adaptive strategies, the modifications of the mathematical definition is required to improve the identification ability. This modified formal definition of the adaptive strategies would advance us to design the robust strategy for other strategies.

6. **Conclusion.** We proposed a concept of an adaptive strategy that earns the higher payoff against itself and other strategies. We also proposed a formal measure of the adaptive strategy, which includes factors of cooperation against other strategies, and self-tolerance. The measure would be small for selfish strategies because of their selfish behavior. We examined the concept of the adaptive strategies for a self-repairing network. In some cases, the highest adaptive measures are different from those having the highest averaged resources. The proposed measurement for adaptive strategies enables us to evaluate the robustness of the strategies against other agents. This paper discussed some open problems to be solved for polishing a notion of the adaptive strategies. We need to consider the condition in which the adaptive strategy maximizes its measure and corresponds to strategies achieving the highest payoffs. The identification ability of the adaptive strategies is also necessary to be modified for improving quantification of the strategies.

Acknowledgements. This work was supported by Grant-in-Aid for JSPS Fellows. This work was also partly supported by Grants-in-Aid for Scientific Research (B): "Foundation on Immunity-Based Complex Systems and Sensor Agents" (23300057) 2011.

REFERENCES

[1] R. Axelrod, *The Evolution of Cooperation*, Basic Books, New York, 1984.

[2] I. Caragiannis, C. Kaklamanis, P. Kanellopoulos, M. Kyropoulou and E. Papaioannou, The impact of altruism on the efficiency of atomic congestion games, *Proc. of the 5th International Conference on Trustworthly Global Computing*, pp.172-188, 2010.

[3] P.-A. Chen and D. Kempe, Altruism, selfishness, and spite in traffic routing, *Proc. of the 9th ACM Conference on Electronic Commerce*, New York, NY, USA, pp.140-149, 2008.

[4] M. Doebeli and C. Hauert, Models of cooperation based on the prisoner's dilemma and the snowdrift game, *Ecology Letters*, vol.8, no.7, pp.748-766, 2005.

[5] I. Dostalkova and P. Kindlmann, Evolutionarily stable strategies for stochastic processes, *Theor Popul Biol*, vol.65, no.3, pp.205-210, 2004.

[6] Y. Ishida, Immunity-based systems: A design perspective, *Advanced Information Processing*, 2004.

[7] Y. Ishida, A critical phenomenon in a self-repair network by mutual copying, *Lecture Notes in Computer Science*, vol.3682, pp.86-92, 2005.

[8] Y. Ishida and T. Mori, Spatial strategies in a generalized spatial prisoner's dilemma, *Artificial Life and Robotics*, vol.9, no.3, pp.139-143, 2005.

[9] Y. Ishida and M. Tokumitsu, Asymmetric interactions between cooperators and defectors for controlling self-repairing, *Lecture Notes in Computer Science*, vol.5179, pp.440-447, 2008.

[10] Y. Ishida and M. Toshikatsu, A network self-repair by spatial strategies in spatial prisoner's dilemma, *Lecture Notes in Computer Science*, vol.3682, pp.79-85, 2005.

[11] E. Koutsoupias and C. H. Papadimitriou, Worst-case equilibria, *Computer Science Review*, vol.3, no.2, pp.65-69, 2009.

[12] M. A. Nowak and R. M. May, Evolutionary games and spatial chaos, *Nature*, vol.359, pp.826-829, 1992.

[13] M. A. Nowak and R. M. May, The spatial dilemmas of evolution, *International Journal of Bifurcation and Chaos*, vol.3, no.1, pp.35-37, 1993.

[14] M. Oohashi and Y. Ishida, Game theoretic approach to regulating mutual repairing in a self-repairing network, in *Innovative Algorithms and Techniques in Automation, Industrial Electronics and Telecommunications*, T. Sobh et al. (eds.), Netherlands, Springer, 2007.

[15] A. Pelc, Fault-tolerant strategies in the iterated prisoner's dilemma, *Inf. Process. Lett.*, vol.110, pp.389-395, 2010.

[16] T. Roughgarden, Stackelberg scheduling strategies, *Proc. of the 33rd Annual ACM Symposium on Theory of Computing*, pp.104-113, New York, NY, USA, 2001.
[17] T. Roughgarden and E. Tardos, How bad is selfish routing? *Journal of the ACM*, vol.49, no.2, pp.236-259, 2002.
[18] J. M. Smith, *Evolution and the Theory of Games*, Cambridge University Press, Cambridge, UK, 1982.
[19] M. Tokumitsu, Adaptive strategies: Toward a design of adaptive systems for dynamic environments, *Proc. of the International Conference on Management of Emergent Digital EcoSystems*, 2011.
[20] J. W. Weibull, *Evolutionary Game Theory*, The MIT. Press, 1997.