Behavioral Characteristics of Humanoid Robot to Suppress Bullying in School

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ABSTRACT

The number of bullying recognition at school is increasing every year, and it is a very serious problem in Japan. The cause of bullying is attributed to the fact that students have independent values in group or classroom and they interact in a complicated way. Therefore, in this research, we added special agents as "Humanoid Robots" to *agent-based model of bullying*, and verified what behavioral characteristics of Humanoid Robots are effective to suppress bullying by using Multi-Agent Simulation. Also, we set six behavioral characteristics on Humanoid Robots in this research. As a result, it was found that the action, "When the number of candidates for bullying exceeds a certain number, a tuning action is caused to a person with a small number of selected values. And if the number of bullying candidates becomes less than a certain number, a tuning action is caused to a person who is the bullying candidate", is most effective against bullying problems.

KEYWORDS

Bullying, School, Humanoid Robot, Multi-Agent Simulation

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1 INTRODUCTION

According to the survey[1] conducted by Ministry of Education, Culture, Sports, Science and Technology (MEXT) in Japan, the number of bullying recognized in elementary school, junior high school, high school and special support school in 2015 was 224,540. This figure increased by 36,468 from the previous year 188,072. The breakdown of the number of bullying recognized is 151,190 in elementary school, 59,422 in junior high school, 12,654 in high school and 1,274 in special support school. The number of schools that recognized bullying was 23,528, which accounted for 62.0% of the total number of schools. This survey indicates the seriousness of the bullying problem in Japan.

In this research, we focused on Humanoid Robot as an approach to the bullying problem at school. There are two reasons for this. The first reason is that "Humanoid Robots can set arbitrary values and behaviors". It is said that bulling is occured by complex interaction of independent values of students in class[2]. The fact "about 80% of bullying is carried out by students in the same class" is attributable to this[3]. Therefore, we thought that it would be possible to control values of students by setting arbitrary values on Humanoid Robot and interacting with students in class. The second reason is that "Humanoid Robots are resistant to receiving bullying". It is said that the balance of forces in bullying is always fluid and it is possible for the relationship between the bullying side and the bullied side to change[4]. Also, it is the common phenomenon that a person intervening to stop bullying become the bullied side, and a lot of people fear this to become a bystander of bullying[3]. Therefore, we thought that Humanoid Robots are resistant to receiving bullying (have no feelings) and they can intervene in bullying without becoming a bystander of bullying.

In response to the bullying problem, Akasaka[5][6] captured bullying at school as *two-dimensional internal and external structures in the community* and modeled the bullying problem with those who were to be bullied as *foreigners inside the community.* Based on this model, Maeda[7] proposes the agent-based model of bullying caused by *value selection and exclusion* against the diversity of value of agents (students) constituting a community (class) at school, and bullying is caused by exclusion action on values of agents. Therefore, in this research, we added special agents (Humanoid Robots) having behavioral characteristics different from ordinary agents to this agent-based model, and examine what kind of behavioral characteristics of Humanoid Robots are effective in suppressing bullying. In the simulation of this research, we used *artisoc*[8] which is Multi-Agent Simulator (hereinafter called MAS).

2 MODELING BULLING

2.1 Value Array

It is required three elements *acceptable space of bullying*, *impulse of bullying*, and *varnerability* for the occurrence of bullying. In addition, it is said that bullying will not occur if suppression power works on any of these elements[9]. We modeled bulling at school using three elements of bulling above. First, let N be a set composed of agents in *acceptable space of bullying*. Next, assign each agents i as identification ID, and let A_i be an arbitrary agent in N. Also, each agents randomly selects m values from the *value array* v composed of M different values.

Here, let $v_i(\varphi) = 1$ be when the agent A_i selects the φth value from the value array v, and let $v_i(\varphi) = 0$ be when the agent A_i does not select the φth value from the value array v. We refer to the sum of values selected from the value array v by the agent A_i as *the number of selected values*, and this is denoted by m_i.

The agent A_i randomly selects one agent $A_j(i \neq j)$ and causes specific actions. Here, we refer to the side of the agent taking action as *action agent*, and let *act* be identification ID. On the other hand, we refer to the side of the agent receiving action as *object agent*, and let *obj* be identification ID. At this time, we refer to the φth value from value arrays v between the agent A_{act} and the agent A_{obj} that satisfy the following equation as *shared value*.

$$v_{act}(\varphi) = 1 \textit{ and } v_{obj}(\varphi) = 1 \tag{1}$$

Also, we refer to the set of shared values of both agents as *the number of shared values*, and this is denoted by $c(act, obj)$. The number of shared values is given by the following equation.

$$c(act, obj) = \sum_{\varphi=1}^{M} v_{act}(\varphi) \cdot v_{obj}(\varphi) \tag{2}$$

The number of shared values means "the psychological distance between two agents", that is, *varnerability*. In particular, the greater number of shared values, the more closer the psychological distance between two agents (hard to be bullied). Also, the smaller number of shared values, the more farther the psychological distance between two agents (easy to be bullied).

2.2 Action of Agents

The agent A_{act} causes *the tuning action* or *the exclusion action* to the agent A_{obj} based on the number of shared values $c(act, obj)$. Here, we refer to the probability of causing these action as *action probability*, and this is denoted by p_{act}. The action probability is given by the following equation using m_{act} of the agent A_{act}.

$$p_{act} = c(act, obj)/m_{act} \tag{3}$$

The action probability means "ease of bulling between two agents", that is, *impulse of bullying*. In particular, it tends to cause the tuning action when the psychological distance is short (the number of shared values is large). Also, it tends to cause the exclusion action when the psychological distance is long (the number of shared values is small). In the previous study[7], let p be the random number from range $[0, 1)$ as *action threshold*, and the action agent A_{act} causes the tuning action to the object agent A_{obj} when $p_{act} \geq p$ is satisfied. In this research, we use the constant number c instead of the random number p, that is, the action agent A_{act} causes the tuning action to the object agent A_{obj} when $p_{act} \geq c$ is satisfied.

The tuning action is an action that randomly choose one value from the value array v and set $v_{act}(\varphi) = 1$ if there is one or more values between the action agent A_{act} and the object agent A_{obj} that satisfy the following equation.

$$v_{act}(\varphi) = 0 \textit{ and } v_{obj}(\varphi) = 1 \tag{4}$$

This action means that "to shorten the psychological distance by tuning with the other's value". However, if the number of selected values m_{act} of the action agent A_{act} exceeds the upper limit m ($m_{act} > m$), adjust m_{act} to $m_{act} = m$ by randomly selecting one value φ satisfying the following equation and setting $v_{act}(\varphi) = 0$.

$$v_{act}(\varphi) = 1 \textit{ and } v_{obj}(\varphi) = 0 \tag{5}$$

In the previous study[7], it was defined that "the exclusion action is an action that the action agent triggers when one discovers a small difference from value arrays with the object agent". In addition, by storing the number of shared values with both agents in each, they can keep differences between the previous number of shared values $c'(act, obj)$ and the current number of shared values $c(act, obj)$. The action agent A_{act} causes the exclusion action to the object agent A_{obj} when the difference of the number of shared values satisfies the following expression and $p_{act} < c$.

$$c'(act, obj) - c(act, obj) \geq d \tag{6}$$

The exclusion action is an action that randomly choose one value from value array v and set $v_{obj}(\varphi) = 0$ if there is one or more values between the action agent A_{act} and the object agent A_{obj} that satisfy the equation (1). In other words, the action agent A_{act} forcibly removes the value (shared value) from the object agent A_{obj}. In this research, we regard the exclusion action as "the action leading to bullying".

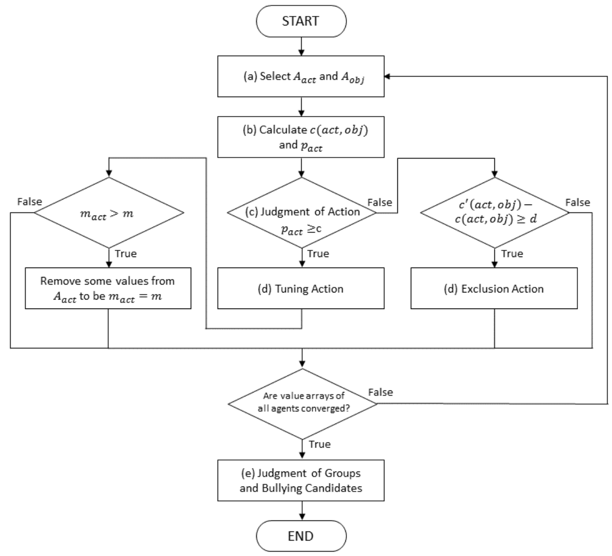

Figure 1: The flow of one simulation

2.3 Simulation Flow

The flow of the simulation is roughly divided into five steps, (a) Selection of two agents, (b) Calculation of shared values and action probability, (c) Judgment of actions, (d) Performing the action, (e) Judgment of groups and bullying candidates. Repeat steps (a) - (d) until all agent's value arrays v converges, and finally perform step (e) as one simulation. Here, the flow of one simulation is shown in Figure 1 and describe all of processes respectively.

(a) Selection of two agents Select two agents (one is the action agent A_{act}, the other is the object agent A_{obj}) at random from the set composed of N agents.

(b) Calculation of shared values and action probability Calculate the shared value $c(act, obj)$ using the equation (2) between the action agent A_{act} and the object agent A_{obj} selected in step (a). Also, calclate the action probability p_{act} of the action agent A_{act} using the equation (3).

(c) Judgment of actions The action agent A_{act} selects tuning action when satisfies $p_{act} \geq c$ in regard to the object agent A_{obj}. On the other hand, the action agent A_{act} selects the exclusion action when satisfies $p_{act} < c$ and the equation (6) in regard to the object agent A_{obj}. Also, the action agent A_{act} does not take any actions when $p_{act} < c$ is satisfied but the equation (6) is not satisfied.

(d) Performing the action The action agent A_{act} causes the tuning action or the exclusion action selected from step (c). Also, if it becomes $m_{act} > m$ due to the tuning action, remove some values from the value array v of the action agent A_{act} until satisfying $m_{act} = m$.

(e) Judgment of groups and bullying candidates The set of agents whose value arrays v completely matches is determined to be the same *group*. Also, an agent whose the value array v does not match with any agent's value arrays v or has $m = 0$ in regard to the number of selected values m is determined as *bullying candidate*.

3 HUMANOID ROBOT

Humanoid Robot is the special agent that causes the tuning action or the exclusion action under different conditions from ordinary agents. In this research, we set six behavioral characteristics described below on Humanoid Robots.

3.1 Perverse Type

Perverse type is a behavioral characteristic that causes the tuning action or the exclusion action under the opposite condition to ordinary agents. In other words, Perverse type takes the exclusion action when it satisfies $p_{act} \geq c$ to the object agent A_{obj}, takes the tuning action when $p_{act} < c$ and the equation (6) are satisfied.

3.2 Tuning Type

Tuning type is a behavioral characteristic with a high probability of causing the tuning action. In order to increase the probability of causing the tuning action, add the supplementary probability *sup* to the action probability p_{act}. In other words, Tuning type takes the tuning action when $p_{act} + sup \geq c$ is satisfied to the object agent A_{obj}, takes the exclusion action when $p_{act} + sup < c$ and the expression (6) are satisfied.

3.3 Exclusion Type

Exclusion type is a behavior characteristic with a high probability of causing the exclusion action. In order to increase the probability of causing the exclusion action, subtract the supplementary probability *sup* from the action probability p_{act}. In other words, Exclusion type takes the tuning action when $p_{act} - sup \geq c$ is satisfied to the object agent A_{obj}, takes the exclusion action when $p_{act} - sup < c$ and expression (6) are satisfied.

3.4 Justice Type

Justice type is a behavioral characteristic that causes *the strong tuning action* when the number of selected values m_{obj} of the object agent A_{obj} is less than or equal to the value threshold *val*, that is, $m_{obj} \leq val$ is satisfied. The strong tuning action means the action that select one value at random from value arrays v between the action agent A_{act} (Justice type) and the object agent A_{obj} and to be $v_{obj}(\varphi) = 1$ if there is at least one value φ satisfying the equation (5) for their value arrays v. However, it will cause the tuning action or the exclusion action under normal conditions if $m_{obj} > val$ is satisfied for the object agent A_{obj}.

Table 1: Parameters of the Simulation

Parameter	Notation	Value1	Value2
The number of agents	N	40	40
The number of values	M	$10, 20, 30, \cdots, 100$	80
The number of selected values	m	10	10
Action threshold	c	$0.1, 0.2, 0.3, \cdots, 1.0$	0.4
Exclusion threshold	d	1	1
Supplementary probability	sup	N/A	0.3
Value threshold	val	N/A	3
Relief threshold	rel	N/A	10
The number of simulations	S	100	100

3.5 Evil Type

Evil type is a behavioral characteristic that causes *the strong exclusion action* when the number of selected values m_{obj} of the object agent A_{obj} is less than or equal to the value threshold *val*, that is, $m_{obj} \leq val$ is satisfied. The strong exclusion action means the action that select one value at random from value arrays v between the action agent A_{act} (Evil type) and the object agent A_{obj} and to be $v_{obj}(\varphi) = 0$ if there is at least one value φ satisfying $v_{obj}(\varphi) = 1$ for their value arrays v. However, it will cause the tuning action or the exclusion action under normal conditions if $m_{obj} > val$ is satisfied for the object agent A_{obj}.

3.6 Relieve Type

The relieve type is a behavior characteristic that causes strong tuning action to the object agent A_{obj} randomly selected from bullying candidates when the number of bullying candidates is less than or equal to the relieve threshold *rel*. However, it will cause tuning action or exclusion action under normal conditions if the number of bullying candidates exceeds the relieve threshold *rel* or $m_{obj} = m$ is satisfied in the selected object agent A_{obj}.

4 SIMULATIONS

4.1 Parameters

The parameters set for MAS are shown in Table 1. The number of agents N was $N = 40$ assuming a real class in school. Also, same values as the previous study [7] were used for the number of values M, the number of selected values m, and the exclusion threshold d. The supplementary probability *sup*, the value threshold *val*, and the relieve threshold *rel* newly added to this study were $sup = 0.3$, $val = 3$, and $rel = 10$ respectively. In addition, the number of simulations S was assumed to be $S = 100$.

In Table 1, there are two values (Value1 and Value2) of parameters. Value1 is parameters that used in the previous study[7]. Here, in our previous study[10][11], it was found that optimum solutions of the combination of the number of values M and the action

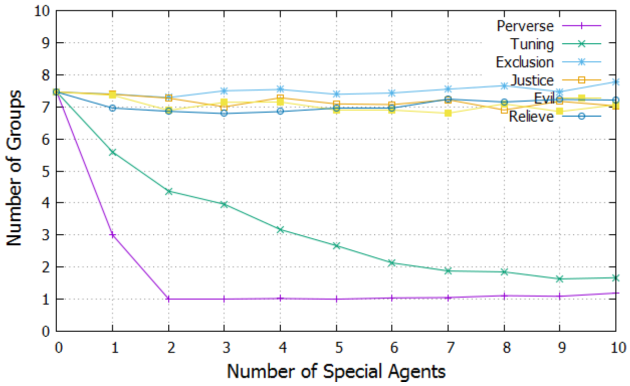

Figure 2: Mean number of groups $\overline{N_G}$

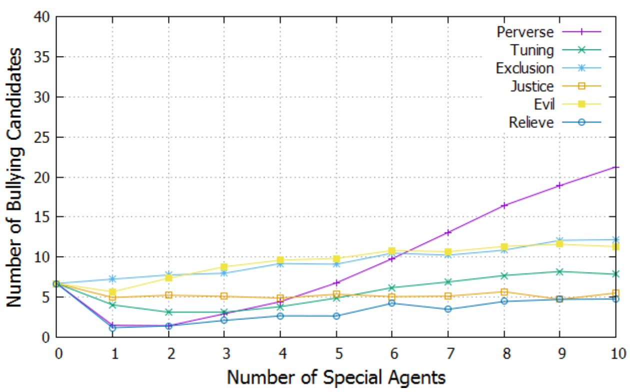

Figure 3: Mean number of bullying candidates $\overline{N_B}$

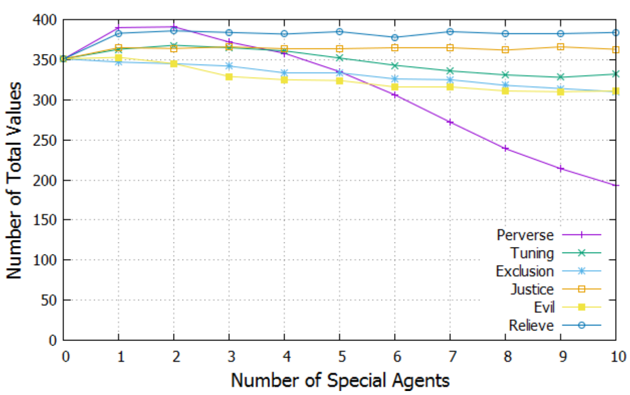

Figure 4: Mean number of total values $\overline{N_V}$

threshold c were 80 and 0.4 respectively. In other words, optimum solutions above means the combination closest to the real class (ideal values), that is, mean number of groups is close to 7, mean number of bullying candidates is as few as possible, and mean number of total values is as mush as possible[12]. Therefore, in this research, we used Value2 instead of Value1.

Table 2: Mean value and standard deviation of the simulation result in the case of including one Humanoid Robot

Type	Groups		Bulling Candidates		Total Values	
	Mean	SD	Mean	SD	Mean	SD
Perverse	3.00	2.53	1.49	1.65	390	10.0
Tuning	5.59	1.47	4.04	2.42	363	16.7
Exclusion	7.40	1.30	7.25	2.79	347	17.2
Justice	7.39	1.57	4.96	2.44	365	13.9
Evil	7.36	1.49	5.67	2.40	353	17.8
Relieve	6.96	1.28	1.19	3.20	383	19.9
(not including)	7.40	1.55	6.61	3.05	350	17.2

4.2 Simulation Result 1

The simulation result in the case of changing the number of Humanoid Robots $N_R = \{0, 1, 2, \cdots, 10\}$ in a group composed N agents is shown in Figure 2-4. In addition, mean value and standard deviation of the simulation result in the case of including one Humanoid Robot ($N_R = 1$) is shown in Table 2. Figure 2 shows mean number of groups $\overline{N_G}$, Figure 3 shows mean number of bullying candidates $\overline{N_B}$, and Figure 4 shows mean number of total values $\overline{N_V}$ (Total number of selected values of all agents) respectively.

First, if we look at Figure 2, we will see that $\overline{N_G}$ of Perverse type and Tuning type decreases markedly with the increase of N_R. On the other hand, there is no big change in $\overline{N_G}$ with the increase of N_R in Exclusion type, Justice type, Evil type, and Relieve type. Next, if we look at Figure 3, we will see that $\overline{N_B}$ of Perverse type, Tuning type, Justice type, and Relieve type is decreasing in the group with $N_R = 1$ compared to $N_R = 0$. Also, it was Relieve type that $\overline{N_B}$ was the lowest result ($\overline{N_B} = 1.19$) among them. However, $\overline{N_B}$ shows an increasing trend with increasing N_R in all cases. This is particularly pronounced in Perverse type. Finally, if we look at Figure 4, we will see that $\overline{N_V}$ of only Perverse type is decreasing with $N_R = 2$, but there is no big change in $\overline{N_V}$ of other types.

Also, as shown in Table 2, it can be said that Relieve type ($N_R = 1$) is the best of types all because mean number of groups is close to 7, mean number of bullying candidates is the lowest, and mean number of total values is high among them. However, standard deviation of bullying candidates in Relieve type is the highest value 3.20. This indicates that the number of bullying candidates in Relieve type is 0 basically, but that becomes very high value if bullying is occurred (It can exceed 10 in some cases).

From these results, it can be said that the class including one Relieve type agent is most effective against bullying problems in the case $N_R = 1$. In other words, it can be said that the behavioral characteristics of Relieve type, "causes strong tuning action to the object agent randomly selected from bullying candidates when the number of bullying candidates is less than or equal to the relieve threshold", is most effective against bullying problems. In addition, it was found that the number of Humanoid Robots does not have mush influence on suppression of bullying, and the number of Humanoid Robots is not as good as it is large.

Table 3: Mean value and standard deviation of the simulation result in the case of including two Humanoid Robots with different type

Type	Groups		Bulling Candidates		Total Values	
	Mean	SD	Mean	SD	Mean	SD
Perverse + Tuning	1.00	0.00	0.37	0.66	396	6.4
Perverse + Exclusion	3.69	2.60	1.93	1.66	385	12.9
Perverse + Justice	2.39	2.23	0.93	1.46	394	9.2
Perverse + Evil	3.65	2.70	3.09	2.37	376	17.6
Perverse + Relieve	1.25	0.98	1.23	0.83	394	7.8
Tuning + Exclusion	5.90	1.54	4.79	2.15	358	14.6
Tuning + Justice	5.69	1.39	2.85	1.91	370	12.8
Tuning + Evil	5.41	1.29	4.49	2.16	355	17.2
Tuning + Relieve	4.65	1.28	0.54	1.49	388	10.1
Exclusion + Justice	7.24	1.44	6.30	2.57	357	13.8
Exclusion + Evil	7.27	1.34	6.54	3.01	349	18.9
Exclusion + Relieve	7.24	1.34	1.67	3.17	380	20.4
Justice + Evil	7.30	1.36	4.39	2.30	367	12.8
Justice + Relieve	6.49	1.35	0.45	0.89	390	7.5
Evil + Relieve	6.69	1.34	1.13	2.11	384	16.3

4.3 Simulation Result 2

Mean value and standard deviation of the simulation result in the case of including two Humanoid Robots ($N_R = 2$) with different type is shown in Table 3.

First, if we look at *Groups* in Table 3, we will see that the values of Perverse + Tuning and Perverse + Relieve are very low. Also, we can get that combinations with Perverse type are low values as a whole. On the other hand, it shows that values of including Exclusion type, Justice type, Evil type, or Relieve type are very high and close to 7. However, if we look at *Bulling Candidates* in Table 3, we will see that most of these combinations are high values. In addition, it can be seen that values including Relieve type in these combinations are very low. In particular, the combination of Justice + Relieve shows the lowest value, mean value is 0.45 and standard deviation is 0.89.

As shown in Table 2, in the case of including one Humanoid Robot of Relieve type, we could get that mean value is 1.19 and standard deviation is 3.20. However, by adding Justice type to this, we found that it is possible to lower mean value and standard deviation. Finally, if we look at *Total Values* in Table 3, we will see that there is no significant decrease in mean value. Especially, Justice + Relieve shows the best value among them.

From these results, it can be said that the class including Justice type and Relieve type agents is most effective against bullying problems in the case $N_R = 2$. In other words, it is found that behavioral characteristics of two agents, "When the number of candidates for bullying exceeds a certain number, a tuning action is caused to a person with a small number of selected values. And if the number of bullying candidates becomes less than a certain number, a tuning action is caused to a person who is the bullying candidate", is most effective against bullying problems.

5 CONCLUSIONS

In this research, we added some special agents as Humanoid Robots to the agent-based model of bullying[7], and verified what behavioral characteristics of special agents are effective to suppress bullying by using MAS. We simulated two pattern, one is the case of including one Humanoid Robot, the other is the case of including two Humanoid Robots with different type.

First, as a result in the case of adding one Humanoid Robot, we found that the behavioral characteristics of Relieve type is the best. In other words, it became clear that the behavioral characteristics, "causes strong the tuning action to the object agent randomly selected from bullying candidates when the number of bullying candidates is less than or equal to the relieve threshold", is most effective against bullying problems.

Next, as a result in the case of adding two Humanoid Robots, we found that the behavioral characteristics of the combination of Justice type and Relieve type is the best. That is, it became clear that the behavioral characteristics, "When the number of candidates for bullying exceeds a certain number, a tuning action is caused to a person with a small number of selected values. And if the number of bullying candidates becomes less than a certain number, a tuning action is caused to a person who is the bullying candidate", is most effective against bullying problems.

Finally, as a future work, we will consider the safety and ethical aspects for students by adding Humanoid Robots to the classroom. If it becomes to be possible, we would like to actually introduce Humanoid Robots into the classroom and examine the suppression effect of bullying.

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