An Agent Control Method based on Rough-Set-based Granularity

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***Abstract*—In this paper, we propose a way of solving conflict resolution in agent control based on rough-set-based granularity. The solution is obtained as the lower approximation of possible actions selected from limited knowledge. Then, we explain how the lower approximation can be generated. In case that the lower approximation is an empty set, variable precision rough set model enables us to obtain the solution of conflict resolution.**

I. Introduction

In behavior-based AI approaches[1], "behavior" is regarded as being more important than "thinking" since an agent in the approach must cope with dynamically changing environments. For the purpose, an agent has to select some actions they should perform through interaction of a number of behaviour modules with a dynamic environment. Such a mechanism of selecting actions is called behavior arbitration.

In this paper, we formulate a method of behavior arbitration on the basis of rough-set-based granularity. We also show simulation results of the proposed method applied in the robot's garbage collection experiment by Ishigro *et al.* [2].

II. Rough Set Theory

Rough set theory originated by Pawlak[4] is one of remarkable methods for discovering knowledge from incomplete or imprecise data. In this section, we give a brief description of some basic notions of rough sets as well as variable precision rough set (VPRS) model proposed by Ziarko[5].

A. Rough Set Theory

Let $I = \langle U, A, V, \rho \rangle$ be an information table, where U is a non-empty finite set, called the universe, of objects, A is a non-empty finite set of attributes, V is a set of value at the attribute $a \in A$, and $\rho : U \times A \to V$ is the function that assigns the value $\rho(x, a) \in V$ of the object $x \in U$ at the attribute a. With any subset $B \subseteq A$ of attributes, we can construct an indiscernibility relation R_B on U by

$$xR_By \overset{\text{def}}{\Longleftrightarrow} \forall a \in B(\ \rho(x, a) = \rho(y, a)\ ).$$

The indiscernibility relation R_B is obviously an equivalence relation on U. The equivalent class $[x]_{R_B}$ of $x(\in U)$ with respect to R_B is denoted by

$$[x]_{R_B} = \{y \in U | xR_By\}.$$

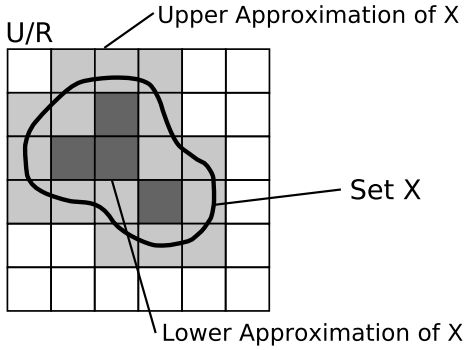

Fig. 1. Rough Set

The set of equivalent classes with respect to R_B provides a partition U/R_B of U.

For a given information system $I = \langle U, A, V, \rho \rangle$, a given subset $B \subseteq A$ of attribute, and any subset $X \subseteq U$, we define the lower approximation of X (denoted by $[R_B]X$) and the upper approximation of X (denoted by $\langle R_B \rangle X$) by

$$\begin{aligned} [R_B]X &= \{x \in U \mid [x]_{R_B} \subseteq X\}, \\ \langle R_B \rangle X &= \{x \in U \mid [x]_{R_B} \cap X \neq \emptyset\}. \end{aligned}$$

A rough set of X is a pair of the lower and upper approximations of X:

$$([R_B]X, \langle R_B \rangle X).$$

B. Variable Precision Rough Set Model

VPRS model proposed by Ziarko[5] is a generalization of rough sets in order to solve the problem that lower approximations have a tendency to be empty because of incompleteness and/or imprecision of given knowledge.

First, $c(X, Y)$, called relative classification error, is defined by

$$c(X, Y) = \begin{cases} 1 - \dfrac{|X \cap Y|}{|X|}, & \text{if } |X| > 0, \\ 0, & \text{otherwise}, \end{cases}$$

where X and Y are subsets of U. The rough inclusion can be difined by

$$X \overset{\beta}{\subseteq} Y \overset{\text{def}}{\Longleftrightarrow} c(X,Y) \leq \beta,$$

where $\beta (0 \leq \beta < 0.5)$ is precision.

Let $U/R_B = \{E_1, E_2, \ldots, E_m\}$ be a partition generated by equivalence relation R_B. Then, the β-lower approximation of X and the β-upper approximation of X are respectively defined by

$$\begin{aligned} [R_{B,\beta}]X &= \bigcup \{E \in U/R_B \mid E \overset{\beta}{\subseteq} X\} \\ &= \bigcup \{E \in U/R_B \mid c(E,X) \leq \beta\}, \\ \langle R_{B,\beta} \rangle X &= \bigcup \{E \in U/R_B \mid c(E,X) < 1-\beta\}. \end{aligned}$$

III. Behavior Arbitration and Rough-Set-Based Granularity

In this section, we formulate a way of behavior arbitration on the basis of rough-set-based granularity. The central issue of behavior-based AI is that an agent can select adapted behavior by perceptual information. It is impossible that the agent knows the true adapted action X. Thus, the agent must approximate X by limited knowledge. The lower and upper approximations of X are constructed by using behaviour modules and a relation among behaviour modules.

A. Behaviour Modules

P_{all} is the set of all possible pieces of perceptual information. A_{all} is the set of all possible actions. P is the current subset of P_{all}. A is the current subset of A_{all}. The behavior module set G_{all} is a subset of the cartesian product $P_{all} \times A_{all}$. One behavior module is a pair $\langle p, a \rangle = g \in G_{all}$. This is a pair of a precondition and an action.

B. Relation Among Behaviour Modules

In behavior-based AI approaches, an agent has to select some actions they should perform through interaction of a number of behaviour modules with a dynamic environment. For the interaction, a binary relation between behaviour modules is defined. The binary relation R_{all} on G_{all} is written as $R_{all} \subseteq G_{all} \times G_{all}$.

By the proposed behavior arbitration method, inclusion degree of each action a_i is given. The inclusion degree is denoted by $\alpha(a_i)$. α is the mapping from A to $[0,1]$.

The action that the agent should perform is one of the elements in $X \subseteq A = \{a_1, a_2, \ldots, a_m\}$, but is unknown so the agent must select one, however, it is, in general, hard so he must make some approximation of X. For precision β, the β-lower and the β-upper approximations are defined using the inclusion degree by

$$\begin{aligned} [R_{a,\beta}]X &= \bigcup \{a \in A \mid \alpha(a) > \beta\}, \\ \langle R_{a,\beta} \rangle X &= \bigcup \{a \in A \mid \alpha(a) \geq 1-\beta\}. \end{aligned}$$

In case $\beta = 0$, this is an original rough set. X is approximated by $[R_{a,\beta}]X \subseteq X \subseteq \langle R_{a,\beta} \rangle X$. Now the agent can select one action from the β-lower approximation.

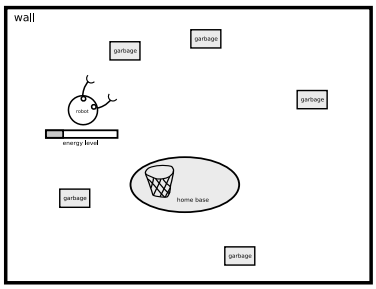

Fig. 2. The robot's garbage collection problem: simulation environment

IV. Robot's Garbage Collection Experiment by Ishiguro *et al.*

Ishigro *et al.* [2] proposed a method of dynamic behavior arbitration and applied it to robot's garbage collection experiment.

In their application, the following correspondence is considered between immune systems and behavior arbitration:

- perceptual information $\Leftrightarrow$ antigens,
- behaviour modules $\Leftrightarrow$ antibodies,
- relation among behaviour modules $\Leftrightarrow$ immune networks.

Each antibody has its concentration parameter and agents can select the antibody that has the highest concentration (see [2] for details). Isigro *et al.*[2] reported the validity of their method by robot's garbage collection problem:

- There exist, a robot, a number of garbages and a home base.
- The space is surrounded by walls.
- The home base is the place where the robot should collect garbages.
- In the home base, the robot can charge energy.

The purpose of the robot is to collect as many of garbages as possible to the home base. The robot can carry only one garbage at a time. Therefore, when the robot is carrying a garbage, other garbages are obstacles for the robot. For each action, the robot loses energy. In particular, the robot loses much energy when it is carrying a garbage.

If the robot have no energy, it freezes. For this reason, the robot must select one suitable action depending on the environment:

- If the robot's energy is high, the robot is required to carry garbages aggressively.
- If the robot's energy is low, the robot is required to search the home base to charge energy.

The simulations in [2] showed that the robot can select adapted actions.

V. A Robot Control Method Based on Rough-Set-Based Granularity

A. Procedure of Behavior Arbitration

The robot has a behaviour module set G_{all} and a relation between behaviour modules R_{all}. In the method, the current behaviour module set is limited to $G \subseteq P \times A$. The current

set of relations between behaviour modules is also limited to $R \subseteq G \times G$. Procedure of the proposed behavior arbitration method is as follows:

step1 Determine the set of behaviour modules G by the current perceptual information P.

step2 Write out the set A_{g_i} of actions that are transitively accessible from each g_i by relation R.

step3 Calculate the inclusion degree of each action: $\alpha(a) = \frac{N}{|G|}$. N is the number of A_{g_i} that satisfies $a \in A_{g_i}$.

step4 For a given β, construct the β-lower approximation by inclusion degree, and select one action from the β-lower approximation.

B. Example

We consider the following two situations:

Case1:
(garbage = front)and(home base = right)and(energy = hi)
Case2:
(garbage = front)and(home base = right)and(energy = low)

In Case1, the robot is required to select action, "catch garbage". In Case2, the robot is required to select action, "search home base" because the robot should charge energy.

We show that the robot using the proposed method can perform the above two actions required.

First, we discuss about original rough set case ($\beta = 0$). The robot has behaviour modules (TABLE I) and a relation among behaviour modules (TABLE II). For simplicity, we rename each action as follows: (turn right) = a_1, (catch garbage) = a_2, (search home base) = a_3, (catch garbage) = a_4. Let X be the currently unknown true action that the robot wants to know.

In case (energy = high)

At present, we have P = {(garbage = forward), (home base = right), (energy = high)}, G = {rule1, rule2, rule4}. G gives R = {firing rule1, firing rule4}.

Let A_{g_i} be the set of actions that are transitively accessible from each behaviour module. In this case, A_{g_i} is obtained in the following way:

- $A_{\mathrm{rule1}} : \{a_1, a_2, a_4\}$
- $A_{\mathrm{rule2}} : \{a_2\}$
- $A_{\mathrm{rule4}} : \{a_2, a_4\}$

TABLE I
G_{all} (BEHAVIOUR MODULES)

rule1 : IF (home base = right) THEN (turn right)
rule2 : IF (garbage = forward) THEN (catch garbage)
rule3 : IF (energy = low) THEN (search home base)
rule4 : IF (energy = hi) THEN (catch garbage)

TABLE II
R_{all} (RELATION AMONG BEHAVIOUR MODULES)

firing rule1 : rule1 → rule4
firing rule2 : rule2 → rule3
firing rule3 : rule3 → rule1
firing rule4 : rule4 → rule2

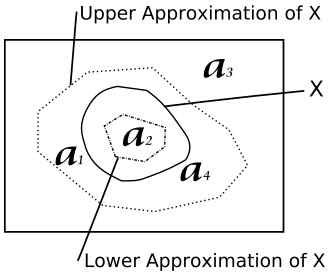

Fig. 3. The lower and upper approximation of X in case (energy = high)

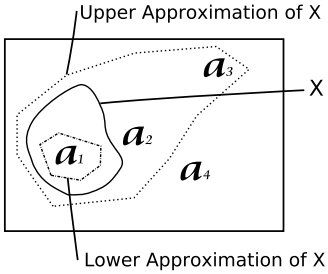

Fig. 4. The lower and upper approximation of X in case (energy = low)

The inclusion degrees of each action are $\alpha(a_1) = 1/3$, $\alpha(a_2) = 3/3$, $\alpha(a_3) = 0/3$, and $\alpha(a_4) = 2/3$. The lower approximation of X is $\{a_2\}$, and the upper approximation of X is $\{a_1, a_2, a_4\}$. X is approximated as follows:

$$\{a_2\} \subseteq X \subseteq \{a_1, a_2, a_4\}$$

With the lower approximation, the robot selects one action "catch garbage". The lower and upper approximations of X in this case are shown in Fig. 3.

In case (energy = low)

At present, we have P = {(garbage = forward), (home base = right), (energy = low)}, G = {rule1, rule2, rule3}. G gives R = {firing rule2, firing rule3}.

In this case, A_{g_i} is obtained as follows:

- $A_{\mathrm{rule1}} : \{a_1\}$
- $A_{\mathrm{rule2}} : \{a_1, a_2, a_3\}$
- $A_{\mathrm{rule3}} : \{a_1, a_3\}$

The inclusion degrees of each action are $\alpha(a_1) = 3/3$, $\alpha(a_2) = 1/3$, $\alpha(a_3) = 2/3$, and $\alpha(a_4) = 0/3$. The lower approximation of X is $\{a_1\}$, and the upper approximation of X is $\{a_1, a_2, a_3\}$. X is approximated as follows:

$$\{a_1\} \subseteq X \subseteq \{a_1, a_2, a_3\}$$

With the lower approximation, the robot selects one action "turn right". The lower and upper approximations of X in this case are shown in Fig. 4.

C. Introducing VPRS

We discuss the original rough set case ($\beta = 0$) illustrated above. It is, however, possible that any lower approximation is empty in case $\beta = 0$. For example, A_{g_i} is obtained as follows:

- $A_{g_1} : \{a_1\}$

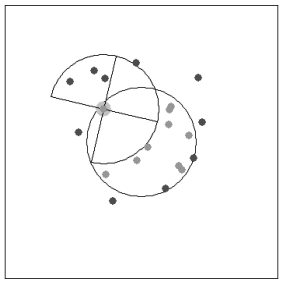

Fig. 5. Simulation image

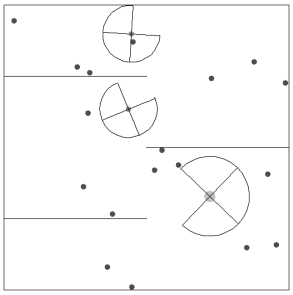

Fig. 6. Dynamic environment

- $A_{g_2} : \{a_1, a_2, a_3\}$
- $A_{g_3} : \{a_1\}$
- $A_{g_4} : \{a_2\}$

The inclusion degrees of each action are $\alpha(a_1) = 3/4$, $\alpha(a_2) = 2/4$, $\alpha(a_3) = 1/4$, and $\alpha(a_4) = 0/4$. If $\beta = 0$, the lower approximation is empty. Let $\beta = 1/4$, then we have the following lower and upper approximations:

$$\{a_1\} \subseteq X \subseteq \{a_1, a_2\}$$

VI. Simulation

We carried out some simulations using the proposed method (Fig 5), by which we confirmed the following four points:

- The robot doglegs walls.
- If the robot does not keep a garbage, the robot go to catch a garbage.
- If the robot keeps a garbage, the robot search home base and go to put it.
- If the robot's energy is low, the robot ignores garbages.

The distinguished merit of behavior-based AI is an ability of prompt response to dynamically changing environments. The simulation above, however, is the static environment. So we must carry out other simulation in dynamic environments (Fig 6), where there are bugs escaping from the robot. In the new simulation, we observed tracking behavior of the robot.

A. Deadlock problem and adjusting the granularity

In these simulations, some deadlock problems arose. For example, when the robot faces the situation that wall is left, right and front, the robot selects two actions (turn right) and (turn left) over and over again, and gets stuck (Fig. 7). In this simulation, to overcome this deadlock, let us consider adjustment of robot's range of view. If the robot detects the deadlock, it reduces its range of view. By reducing the range, the number of visible walls decreases and the robot can escape from the deadlock (Fig. 8).

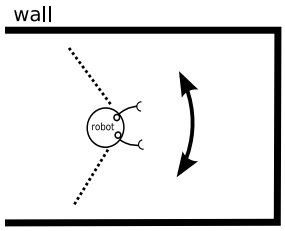

Fig. 7. Deadlock problem

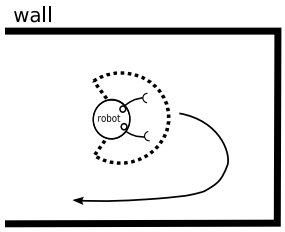

Fig. 8. Adjusting of range of view

The adjustment of perceptual information depending on the situation is possibly effective in some cases and the robot is expected to be able to behave smoothly.

VII. Conclusion

In this paper, we formulated a new approache to behavior arbitration in behavior-based AI on the basis of rough-set-based granularity by constructing lower approximations. We carried out some simulations in robot's garbage collection experiment by Ishiguro *et al.*[2] and confirmed that the robot selected adapted behavior.

To overcome the deadlock problem, we introduced adjustment of perceptual information. We plan to discuss about some effects of this sort of adjustment on the behavior arbitration with the rough-set-based granularity.

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