Perception-action rule acquisition by coevolutionary fuzzy classifier system

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Abstract

Recently, many researchers have studied for applying Fuzzy Classifier System (FCS) to control mobile robots, since the FCS can easily treat continuous inputs, such like sensors and images by using fuzzy number. By using the FCS, however, only reflective rules are acquired. Thus, in proposed approach, an additional Genetic Algorithm in order to search for strategic knowledge, i.e., the sequence of effective activated rules in the FCS, is incorporated. That is, proposed method consists of two modules: an ordinal FCS and the Genetic Algorithm. Computational experiments based on WEBOTS, one of Khepera robots' simulators, are confirmed us the effectiveness of the proposed method.

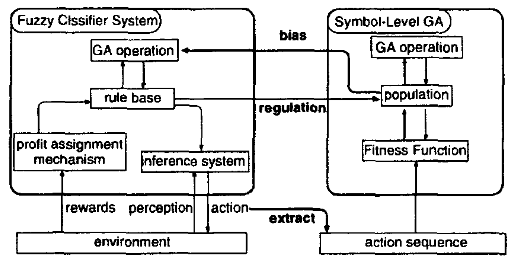

Figure 1. A schematic description of Coevolutionary Fuzzy Classifier System

1. Introduction

Recently, sequential decision making problems under uncertain environments such that agents learn the perception-action rules based upon their experience acquired by interacting with the environment have been studied by many researchers. As a solution of such problems, Fuzzy Classifier Systems (FCS) which is one of the machine learning techniques has been widely adopted. The FCS can easily manipulate continuous inputs due to its fuzzy processing. However, knowledge acquired by the FCS is just reactive. It is very important for good decision making not only to acquire good perception-action rule sets against each situation but also to extract and exploit strategic knowledge or meta-knowledge for effective achievement of tasks. In this paper, we propose a new fuzzy classifier system utilizing the mechanism of co-evolution in order to acquire and utilize such strategic knowledge effectively.

Since such strategic knowledge is a kind of tacit knowledge and is difficult to use in computers, we simply regard strategic knowledge as a sequence of effective activated rules in this paper.

In this paper, we propose a new fuzzy classifier system utilizing the mechanism of co-evolution. That is, proposed method consists of an ordinal FCS module and a Symbol-Level Genetic Algorithm (SLGA): the FCS moudle by Michigan Approach serves as a decision maker of an agent, that is, the FCS module percepts the sensory inputs from environment, chooses his action, and then, affects for the environment by chosen action. On the other hand, the SLGA module searches for effective activated rule-sequence, i.e., strategic knowledge in order to achieve the agents' task effectively. Hence, the sequences of rule indices in rule set of the FCS module is adopted as the coding method of SLGA module.

In next section, we will explain the proposed method. Then, several simulations on WEBOTS which is a kind of Khepera robots' simulator are carried out. Finally, this paper will be concluded.

```
Procedure CoevolutionaryFuzzyClassifierSystem
begin
  Perception;
  Matching;
  ActionSelectionFromMatchedRules;
  RefinforcementForClasifierModule;
  if Count mod GA_Interval = 0 then begin
    EvaluateIndividualsInSLGA;
    GenticSearchOfRulesInClassiferModule;
    EvolutionOfSLGA;
  end
end
```

Figure 2. Pseudo code for our Coevolutionary Fuzzy Classifier System

2. Coevolutionary Fuzzy Classifier System

2.1 Overview

The sketch and pseudo-code of the proposed method are described in Fig. 1 and Fig. 2, respectively. As depicted in Fig. 1, the proposed method consists of two modules: an ordinal Fuzzy Classifier System and a Symbol-Level Genetic Algorithm. The FCS module is a kind of Michigan Approach Classifier System, and adapts for unknown environment. Namely, the FCS module learns which rule is effective for each situation. On the other hand, the SLGA searches for the effective sequence of activated rules in the FCS module. In this paper, we regard such sequence as strategic knowledge or meta knowledge for agent in order to accomplish his task. Thus, the coding method of the SLGA is described as follows: the length of each chromosome is fixed in advance, and the allele of each gene is constituted by the rule indices in the rule sets of the FCS. Moreover, as delineated in Fig. 1, three kinds of the interactions between these modules are introduced as follows:

extraction The extraction indicates that the fitness of SLGA-individuals is evaluated by observing actual sequences of activated rules.

regulation The alleles of SLGA are regulated by the rule sets in the FCS module because they are consisted by the rule indices of the FCS module.

bias Rules included in the effective rule sequences searched by the SLGA are protected in "GeneticSearchOfRulesInClassifierModule" in Fig. 2.

Namely, first, rule indices written in SLGA-individual which have higher fitness values in the SLGA population are chosen as biased rule. Then, rules in the FCS module which are biased by the SLGA are preferentially survived to next generation such like the elitist selection. In following subsections, we concretely introduce the mechanism of each module.

2.2 Fuzzy Classifier System Module

This FCS module is just ordinal Fuzzy Classifier System, that is, it consists of a Fuzzy Rule Base, an Inference Engine and Profit Assignment Mechanism. Furthermore, the Fuzzy rule base has rule set whose rules are represented by fuzzy number. The Inference Engine regards such fuzzy number as the membership function so that action supported by each rule is inferred by using percepted information and input parts of rule, i.e., fuzzy number. The Inference Engine, moreover, outputs actual control to actuator by selecting the supported action value of rule with the best matching score against current perceptual inputs. Finally, the Profit Assignment Mechanism serves as a mean of reinforcing the strength utilizing reward information based on agents' action. Although several profit assignment mechanisms have been devised, we adopt profit-sharing method, one of basic, standard profit assignment mechanisms: first, activated rules in certain episode are enumerated. Besides, for each activated rule, the strength of it is reinforced in proportion to reinforcements accumulating in the episode as described following equations.

$$Str_i = Str_i + \Delta_i$$

$$\Delta_i = A(i, E) \times \frac{\sum_{t \in E} r_t}{|E|},$$

where i, E, r_t, Str_i, $A(i, E)$ denote the rule index, the set of activated rules in certain episode, reward received by the agent at time step t, and the rule strength of rule i, respectively. In the proposed method, all rules activated in an episode equaly distribute rewards gained in the episode, namely, we don't adopt banked distribution of rewards such that some rules activated at the most recent time tend to get much rewards.

2.3 Symbol-Level Genetic Algorithm

We use a traditional Genetic Algorithm, called SGA, as the Symbol-Level Genetic Algorithm. That is, the SLGA is constituted by roulette wheel selection, 2-point crossover, and mutation. As we mentioned above, the individuals of the SLGA are made up of rule indices with fixed length which represent as action sequence of agents. The fitness of these individuals based on matching for the sequences of activated rules and their strength is calculated as follows:

rule idx in CS	fit. of rule	gene. info. of SLGA	their fit.
0	5		
1	15	012	35
2	10	223	50
3	20		

Observed Action Sequence: 22301223· · ·

Figure 3. fitness evaluation for SLGA-individual

$$F(j) = \gamma N_m + \sum str_i$$

where, γ, str_i and N_m denote some coefficient, the strength of rules i supported by a SLGA-individual, and the number of matching between the action sequence and the SLGA-individual. Suppose that rule sets in the FCS module, genetic information of SLGA-individuals, and observed action sequence are followed by Fig. 3. Furthermore, suppose that $\gamma = 5$. Then, as descripted in Fig. 3., the fitness value of first SLGA-individual whose genetic information is represented as "012" is that $5 \times 1 + 5 + 15 + 10 = 35$. On the other hand, the fitness value of another SLGA-individual whose genetic information is represented as "223" is calculated by the same manner, i.e., $5 \times 2 + 10 + 10 + 20 = 50$.

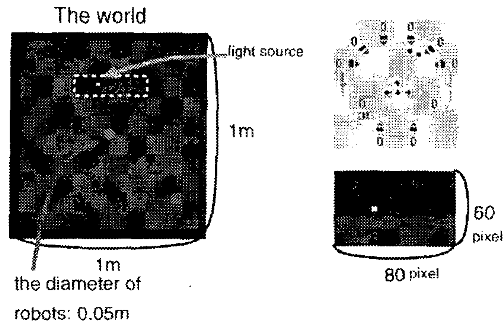

Figure 4. the bird's view of the world (LEFT) and the characteristics of the mobile robots used in this paper (RIGHT)

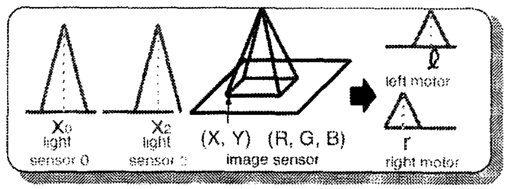

Figure 5. the coding method for fuzzy classifer system against light seeking problem

3. Experiments

3.1 Simulated Environments and Implements

In this paper, we adopt WEBOTS which is a kind of commercial-based Khepera Simulator as simulated environment. However various kinds of environmental settings for simulation can be prepared by using the WEBOTS, simulated environment used in this paper is quite simple as delineated in Fig. 4. The size of the world is $1m \times 1m$. Anywhere in area marked by dashed line, a light source is located. The agent is randomly located near an opposite-side wall as initial position. Moreover, the initial orientation of the agent is fixed randomly. The task of this experiment is to seek the light source. As the same as the real Khepera robot, the agent has eight IR sensors, a CCD camera whose resolution is 60×80 pixels, and two wheels which can be separately actuated. Hence, the coding method for ordinal Fuzzy Classifier system and the FCS module in the proposed method is set to be the same: Each IR sensor in six sensors on the front side is associated to a triangle fuzzy number whose shape is fixed. Therefore, single variable X_i is used to assign the location of the triangle fuzzy number. This single variable X_i might be "don't care symbol." Also, a pyramid fuzzy number is associated for CCD camera. The shape of this fuzzy number is also fixed however this fuzzy number is appended color vector which indicates what color causes the pyramid fuzzy number to activate well. Thus, five variables are needed to represent a pyramid fuzzy number. Furthermore, each actuator is associated to a triangle fuzzy number. As well as the IR sensors, the shape of this fuzzy number is also fixed and is specified by a single gene.

3.2 Results

First, the number of success episodes per 100 episodes is investigated in the case of ordinal Fuzzy Classifier System (FCS) and the proposed method, namely, Co-evolutionary Fuzzy Classifier System (CCS) as depicted in Fig. 6. A vertical axis and a horizontal axis indicate the number of intervals for 100 episodes and the number of success episodes per 100 episodes, i.e. one interval, respectively. Vertical lines in both graphs indicate when a terminal criterion is hold. In this paper, the terminal criterion is set that last five successive intervals, such that the number of success episodes per 100 is greater than 60, are appeared. As depicted these graphs, the proposed method attains the terminal criteria faster than FCS. Next, trajectories to light source for

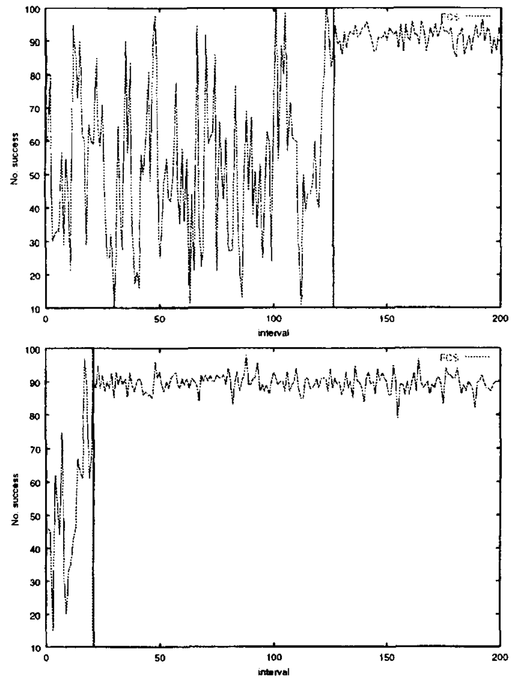

Figure 6. The number of success episodes per 100 episodes; vertical lines in both graphs indicates when a terminal criterion is hold.

each algorithm are examined as delineated in Fig. 7. A vertical axis and a horizontal axis indicate the coordinate of the agent. Solid lines in these graphs denote the trajectory of these algorithms. In this figure, significant distinction between graphs in this figure isn't seen. Finally, the number of activated rules against view angles to the light source is described in Fig. 8. Besides, the number of activated rules biased by the SLGA against view angles to the light source is described in Fig. 9. Horizontal, depth, and vertical axises indicate the view angle to the light source, the variety of action, and the number of activated rules against each view angle. Furthermore, "Photo Rules" and "IR rules" indicate rules which have the highest matching score at fuzzy number for Photo sensor and IR sensor, respectively. As depicted in these graphs, the proposed method can detect effective rules well because "go straight" action is biased when the light source is in the front of the agent, and so on.

4. Conclusion

In this paper, we proposed a novel fuzzy classifier system involving the mechanism of co-evolution. Additive GA introduced the proposed method serves as a

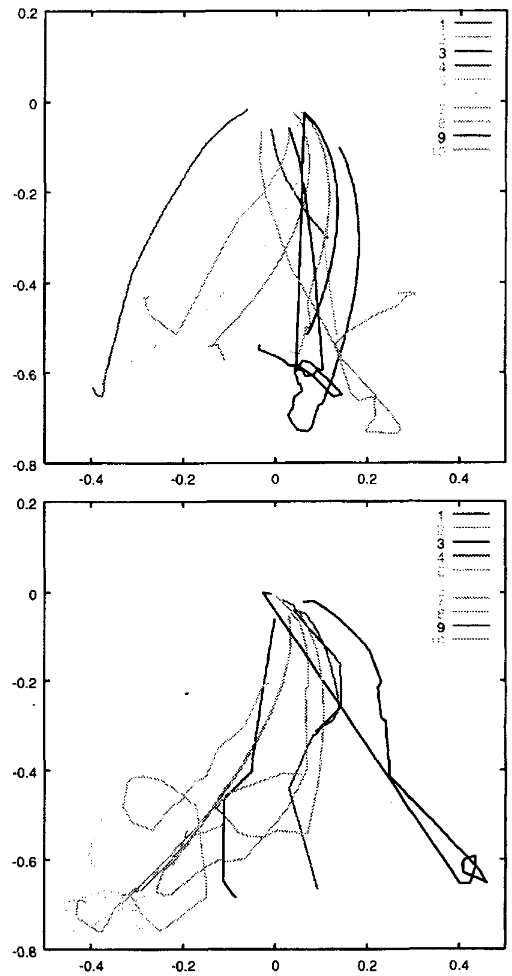

Figure 7. Trajectories for ordinal fuzzy classifier system (UPPER) and the proposed method (LOWER)

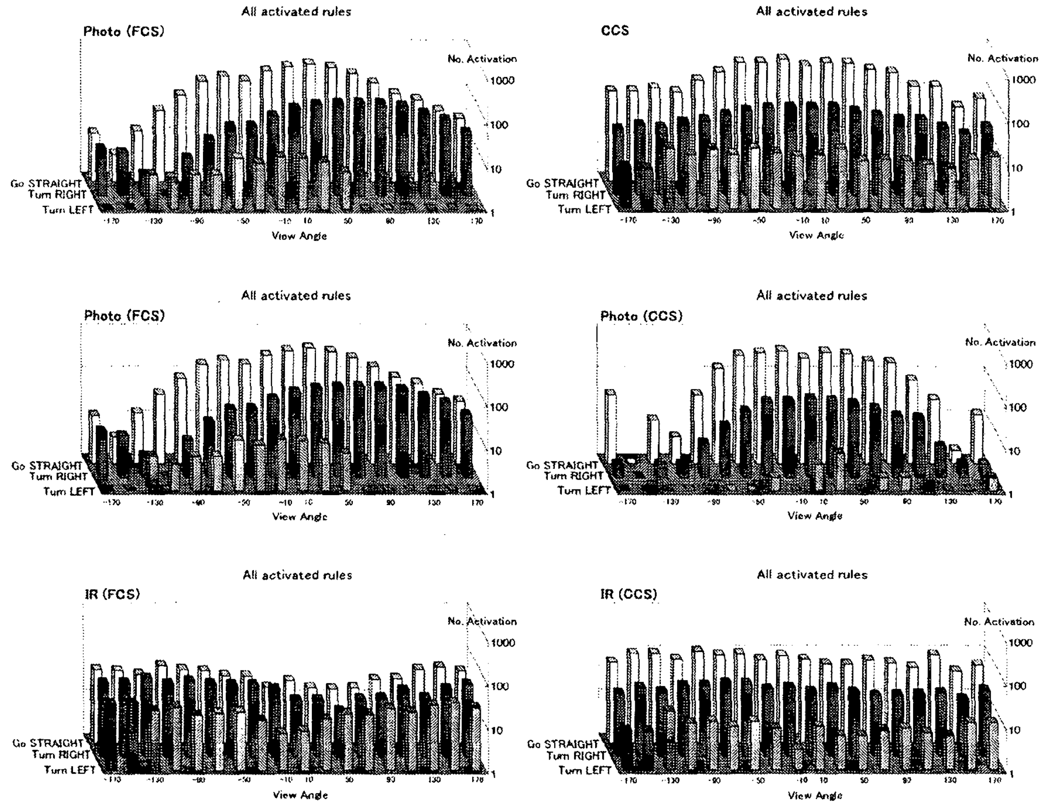

Figure 8. activated rules for ordinal fuzzy classifier system (LEFT) and the proposed method (RIGHT): all rules (UPPER), Photo rules (MIDDLE), IR rules (LOWER),

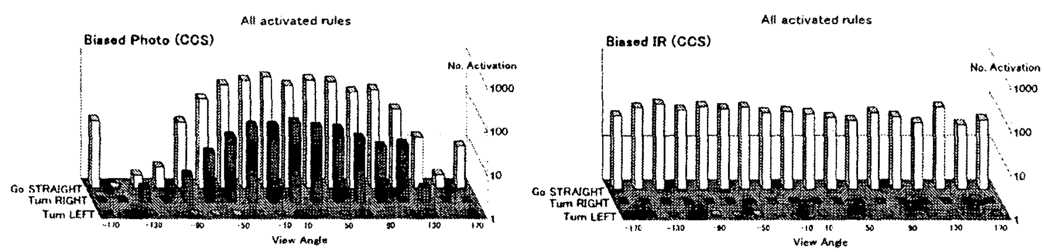

Figure 9. activated rules biased by SLGA; Photo (LEFT) and IR (RIGHT)

mean of acceleration of adaptation of the fuzzy classifier module by detecting effective activated rule sequences. As future work, it is very important to investigate on more complicated tasks such like obstacle avoidance, robocup, and so on.

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