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Co-evolution of Fuzzy Controller for the Mobile Robot Control

Kwang-Sub Byun, Chang-Hyun Park, and Kwee-Bo Sim
School of Electrical and Electronics Engineering, Chung-Ang University
221, Huksuk-Dong, Dongjak-Gu, Seoul 156-756, KOREA
Email:kbsim@cau.ac.kr

Abstract — **In this paper, in order to deduce the deep structure of a set of fuzzy rules from the surface structure, we use co-evolutionary algorithm based on modified Nash GA. This algorithm coevolves membership functions in antecedents and parameters in consequents of fuzzy rules. We demonstrate this co-evolutionary algorithm and apply to the mobile robot control. From the result of simulation, we compare modified Nash GA with the other co-evolution algorithms and verify the efficacy of this algorithm through application to fuzzy systems.**

I. INTRODUCTION

In order to realize autonomous mobile robot, the fuzzy control system has proposed various methods and received large attention for many years. Fuzzy systems use a mode of approximate reasoning, which allows them to make decisions based on vague and incomplete information in a way similar to human beings[1].

Two concepts—a linguistic variable and a fuzzy if-then rule— within fuzzy logic play a central role in its applications. A linguistic variable is interpreted as a label of a fuzzy set that is characterized by a membership function[2]. A fuzzy rule is decomposed into antecedents and consequents that contain linguistic variables. A fuzzy system is able to have robust control of the robot with vague environment and represent apparently a structure of the controller. Also it has many advantages such that the sensitivity to a variation of parameters or noise is low and application is various.

The main problem in the fuzzy system is how to design the fuzzy knowledge base. It is composed of membership functions and fuzzy rules. It is very important to design optimal fuzzy rules and membership functions. It is difficult to design optimal rule base, but there are many different approaches applied to this specific problem: neural networks, fuzzy neural networks, decision trees and evolutionary techniques[3].

In particular, Co-evolutionary algorithms have received increased attention in the past years within the domain of evolutionary computation. A co-evolutionary system has subsystems with ES(Evolutionary Strategy) and the fitness function is playing the role of the cooperation node between each subsystem. The rule base collects the best rules from all subsystems[3].

Another co-evolutionary system generates automatically rules for fuzzy logic controllers using rule-level co-evolution(Michigan approach) of subpopulations. The algorithm induces competition among the rules within the same subpopulation while those in different subpopulations cooperate in harmony to search for the best fuzzy logic controller[4]. The other co-evolutionary system has cooperative co-evolution to the fuzzy modeling(Fuzzy CoCo). It designs optimal fuzzy rules and membership functions using cooperators[5]. Also Nash genetic algorithm is used in a non-cooperative multiple objective optimization approach[6].

In this paper, we coevolve membership functions in antecedents and fuzzy singleton in a consequent using Nash GA that is modified in this paper. Because the proposed co-evolutionary system has fuzzy controller with the simplified method of Sugeno, a consequent in fuzzy rules is represented by a constant. Section II describes the proposed co-evolutionary system. Section III describes an application to behavior of a mobile robot. Section IV then presents the result of experiment. Finally, Section V presents the conclusion.

II. CO-EVOLUTION OF FUZZY CONTROLLER

A. Co-evolution

Co-evolution refers to the simultaneous evolution of multiple species that affect one another. As one species evolves, it changes the relationship with surrounding species. However, evolution of one species could be independent of all other species. Jason Morison classified the co-evolution into seven types and represented them using graph: 1) Commensalism, 2) Amensalism, 3) Mutualism, 4) Competition, 5) Predation, 6) Adaptism, and 7) Indirect and ambiguous types[7].

Among these, Mutualism is a cooperative co-evolution. We design the proposed system using this type.

B. Applying Co-evolution to Fuzzy Control

Zadeh said that a fuzzy rule can have a surface structure or a deep structure[2]. The surface structure is the rule in its symbolic form. Such a rule is said to be uncalibrated, which means that the membership functions of the antecedents and the consequents are not specified. The deep structure is the surface structure with a characterization of the membership functions in linguistic values of variables. In this case, the rule is said to be calibrated. A surface structure is defined according to a problem to which a fuzzy system is applied. It is a deep structure that tuning system has to deduce. Fig. 1 shows the ways to derive the deep structure of a set of rules from the surface structure[2].

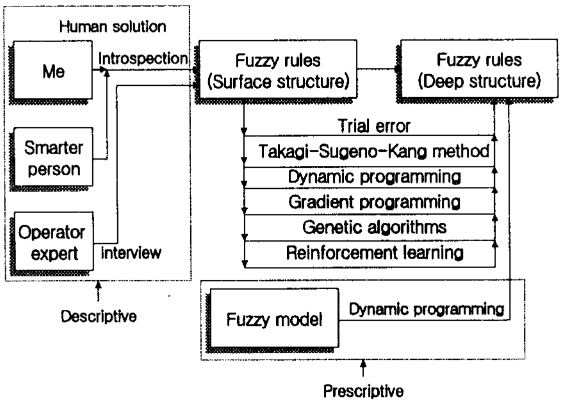

Fig. 1. Methods to deduce the deep structure of a set of rules.

Fuzzy CoCo, proposed by Pena-Reyes and Sipper, is attractive algorithm that evolve cooperatively membership functions and rule base together[5]. However, in point of evolving whole rule base it is not effective because rule base includes the surface structure.

Nash GA has applied in various methods since early 50's[6]. Applied fields are mostly one of non-cooperative models. Each generation, a population is used with the population in previous generation and without initializing. However, this algorithm can have a bad influence to entire system. Thus, in this paper Nash GA is modified—a population that is evolved is initialized randomly every generation. Also modified Nash GA is applied to the cooperative model.

In this paper, two coevolving species are defined: membership functions of antecedents and parameters of consequents in fuzzy rules. For convenience, assuming that a set of individuals from membership functions of antecedents is the population 1 and a set of individuals from parameters of consequents is the population 2, two populations are initialized randomly in the first step. Fixing the best value of the population 2, the population 1 is evolved until the fitness doesn't further improve. An individual from the population 1 is combined with the fixed best value of the population 2 to construct entire system and then it evaluates the fitness. Thus, the population 1 optimizes individuals from itself. Then, Fixing the best value of the population 1, the population 2 is initialized randomly and is also evolved until the fitness doesn't further improve. Next, when the population 2 is optimized, the population 1 is initialized randomly. Like this, two populations co-evolve. Fig. 2 shows the modified Nash GA.

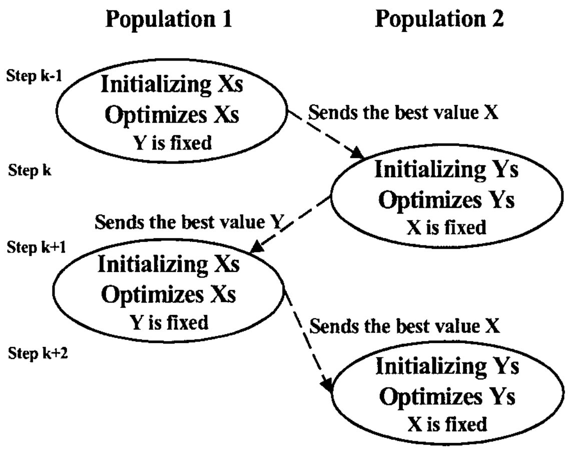

Fig. 2. Modified Nash Genetic Algorithm

III. Application to Behavior of a Mobile Robot

A. Characteristic of a Mobile Robot

We apply the algorithm to a mobile robot with following features. The robot has 12 ultra-sonic sensors that has 10m range. The body of mobile robot has a synchro-drive method with 3 driving wheels. The synchro-drive method is that driving and steering of wheels is accomplished simultaneously and independently. Thus, in order to simplify the application, we utilize only 3 sensors: front, left, and right. Also we assign a fixed value to driving of a robot and we can control only steering.

The environment is the roadway with walls and aisles. The mobile robot moves along by the wall and reaches the aimed point. Inputs of the robot controller are the distance of 3 directions and output is a steering angle of the robot. The robot controller is constructed by a fuzzy system. This system is outlined below.

B. Fuzzy Controller

Generally, fuzzy reasoning methods are various. They are classified to three types: direct method, indirect method, and hybrid method. We use the simplified method of Sugeno in fuzzy reasoning. Simplified method is one of indirect methods[8]. The advantage of this method is that it includes a defuzzifier in the inference engine. Also the feature of this method is that the parameter of consequent is given by a constant. The value of inference result is obtained from following mathematical expression (1). In this expression, λ_i represents the fitness that is obtained from the i_{th} fuzzy rule, c_i represents the constant value of consequent in the i_{th} fuzzy rule and Z represents the final value of output of fuzzy inference.

$$Z = \left(\sum_{i=1}^{n} (\lambda_i \times c_i) \right) / \left(\sum_{i=1}^{n} \lambda_i \right) \qquad (1)$$

Knowing to above expression, the final value is obtained directly from output of fuzzy inference engine. The rule of simplified method has the form:

if X_1 is A_1 and X_2 is A_2 and X_3 is A_3 then Y is b

where $X = (X_1, X_2, X_3)$ and Y are linguistic variables and (A_1, A_2, A_3) and b their respective linguistic values. Especially (A_1, A_2, A_3) are forms of general membership functions and b is a fuzzy singleton in simplified method. Membership functions and a fuzzy singleton b that are used in this application are depicted in Fig. 3. The basic rule for the behavior of a mobile robot has the form:

if *Front Distance* is *Large* and *Left Distance* is *Small* and *Right Distance* is *Large* then *Steering* is *NL*.

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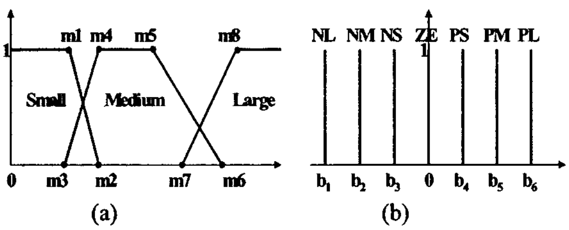

Fig. 3. Linguistic Values (a) Membership Functions and values to calibrated (b) Fuzzy Singletons to calibrated

C. Applying Co-evolution to This Fuzzy Controller

In order to find optimal membership functions and result in optimal fuzzy rules, co-evolutionary algorithm is applied to above fuzzy controller. The fuzzy controller with such a membership functions as Fig. 3 (a) needs eight points: *m1~m8*. If these points are determined, three membership functions of a trapezoidal form are determined as Fig. 3 (a). Also the fuzzy controller with such a constant as Fig. 3 (b) needs seven points: *NL*, *NM*, *NS*, *ZE*, *PS*, *PM*, and *PL*. By the way, *ZE* represents a zero offset and thus, *ZE* is fixed to a zero value. Therefore, if six points are determined, fuzzy singletons for the consequents of fuzzy rules are determined.

The co-evolution defines two species as membership functions and fuzzy singletons. Strictly speaking, One species is a population with individuals from eight points(*m1~m8*) and another species is a population with individuals from six points(*NL*, *NM*, *NS*, *PS*, *PM*, *PL*). Two species evolve independently each other. The process of this co-evolution is depicted in Fig. 2 and Fig. 4. Fig. 4 represents one generation of Fig. 2 in detail.

In step k, a population 1 receives the best individual Y from population 2 and is initialized randomly. The best

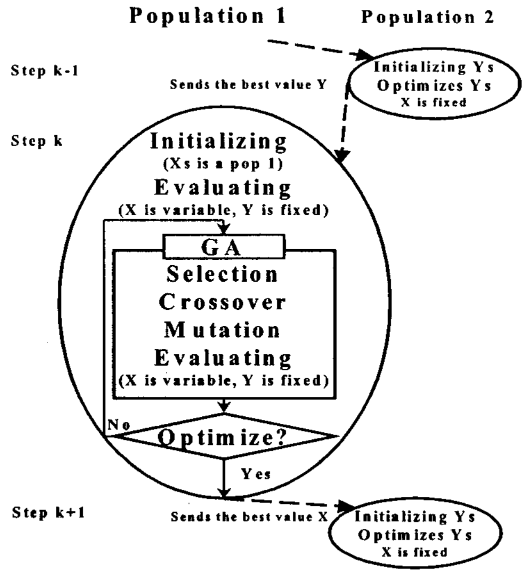

Fig. 4. Optimizing Process in modified Nash GA

value Y is fixed and is combined with individuals(Xs) in the population 1. As a result of this, entire fuzzy system is composed of the population 1 and the population 2. Then, the fitness of fuzzy system is evaluated.

With these individuals, genetic algorithm is performed. Individuals that are reproduced are selected using the roulette wheel selection and the elite preserving selection. Individuals that are selected randomly evolve in a generation through one-point crossover and a general mutation. Entire fuzzy system is composed of the population 1 and the fixed value Y. The fitness of fuzzy system is evaluated and is given to an individual in the population 1. If the condition of termination is satisfied, the population 1 terminates the optimizing process and sends the best value X to the population 2 in step k+1. Otherwise, GA is performed repeatedly. Evaluating the fitness is represented in the following paragraph.

The distance of a robot moving is divided into 11 parts(*pos0~pos11*). The *pos0* represents a start point and the *pos11* does an aimed point. The collision of a robot gives absolutely zero fitness. The more a robot nears the wall, the lower the fitness is given. The fitness function has a form:

$$f = (pos/11) \times (1 - near/50) \qquad (2)$$

where, *near* represents the number of nearing the wall and maximum number of nearing is 50.

IV. Results

In this paper, the computer simulation is performed with the following fixed parameters: Probability of crossover(Pc) is 0.8; probability of mutation(Pm) is 0.05; population size is 70; and the number of generations is 200. Fig. 5 shows the results of experiment for the following algorithms: 1) co-evolution using modified Nash GA, 2) co-evolution using classical Nash GA, 3) co-evolution using Fuzzy CoCo, and 4) general Genetic Algorithm.

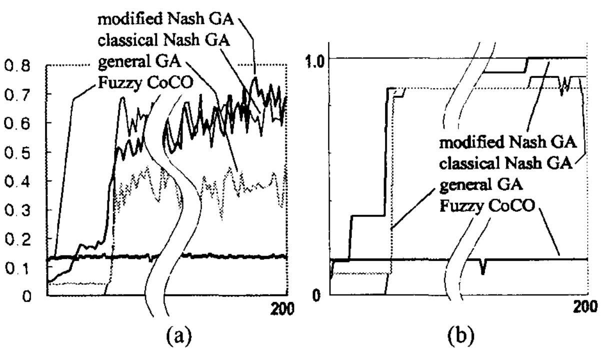

Fig. 5. The Results of experiment (a) average fitness landscapes (b) best fitness landscapes

As shown in Fig. 5, all algorithms except for Fuzzy CoCo is similar in the fitness landscapes, but co-evolution using modified Nash GA is better than any other algorithm in average and best fitness. Fuzzy CoCo using cooperator technique is not likely to be suitable for this application. From this result, applying co-evolutionary algorithm to the fuzzy systems, we can find a best solution as Fig. 6.

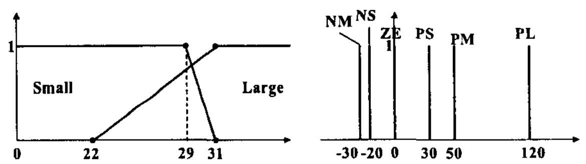

Fig. 6. Best Solution from the Result of Co-evolution

As shown in Fig. 6, the number of parameters—membership functions in antecedent and parameters in consequent— in the fuzzy rule decreases. The individual has the fitness 1.0. Therefore, a mobile robot moves to an aimed point without collision and nearing to the obstacle.

In addition, we made an experiment on co-evolution using modified Nash GA with the best value Y which is randomly created in the first generation of the first step. The result is depicted in Fig. 7. In this case, co-evolution is performed well. This case is only 1 step longer than one with the defined fixed value.

V. Conclusion

As a result of the co-evolution using modified Nash GA, the number of parameters in the fuzzy rule decreases. So, the number of fuzzy rules decreases, too. Finally, the performance of fuzzy controller is advanced in view of speed and cost. Also it is not almost affected by the fixed individuals of population 2 in the first step.

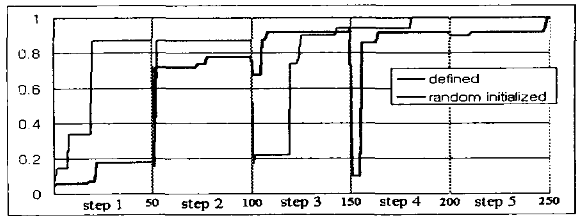

Fig. 7. The best Fitness Landscapes. The 'defined' line represents the algorithm that has the initial fixed value which is defined in the first step and the 'random initialized' represents that it is randomly created.

In this paper, we modified the Nash GA and applied it to cooperative model—designing optimal fuzzy rules for the mobile robot control. It is expected that co-evolutionary algorithm using modified Nash GA is widely used in various fields.

Acknowledgments

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