INTELLIGENT ROBOTS

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Biographical Sketches

Summary

This chapter presents basic ideas and formulation of intelligent techniques including fuzzy, neural, and evolutionary computing, and reinforcement learning to build intelligent robots in unknown or dynamic environments. First, Section 1 presents the history of intelligent systems and robots. Section 2 presents fuzzy computing based on the psychological features of brain, and explains fuzzy logic, fuzzy control, and fuzzy inference. Section 3 presents neural computing based on the physiological features of brain, and explains Perceptron, multilayer Perceptron, backpropagation algorithm, and neural network paradigm. Section 4 presents evolutionary computation simulating natural evolution on a computer, and explains genetic algorithms, evolutionary programming, evolution strategies, and coevolutionary computation. Section 5 presents reinforcement learning methods such as temporal difference learning, Sarsa, and Q-learning. Section 5 discusses the intelligence and functions of robots from the viewpoint of adaptation and evolution.

1. Introduction

Intelligence has been discussed since ancient days. To build intelligent systems, various methodologies have been developed by simulating human behaviors and by analyzing human brains. First, we discuss intelligence from the viewpoint of Cybernetics. Generally, Cybernetics is considered as the theoretical study of communication and control processes in biological, mechanical, and electronic systems. The traditions of cybernetics can be dealt with from the three different viewpoints; Wiener’s Cybernetics, Turing’s Cybernetics, and McCulloch’s Cybernetics. Wiener’s Cybernetics is the study of control system based on the concept of feedback. The computational model for a system is based on the functions, not symbolic representation and manipulation. The feedback analysis is used for discussing the stability of a system. Especially, homeostasis of an organism is discussed as the ability to maintain internal equilibrium or to keep internal balance within suitable ranges by adjusting its physiological processes in a dynamic or open environment. Therefore, ecological, biological, and social systems are also considered as homeostatic. Turing’s Cybernetics is the study of the intelligence on calculation and machine based on computability. A Turing machine is a theoretical model of a computer. Turing’s original aim is to provide a method for evaluating whether a machine can think or not, and Turing discussed digital computers as discrete state machines and learning machines based on education process. McCulloch’s Cybernetics is the study of neuroscience. McCulloch and Pitts suggested a mathematical model of a single neuron as a binary device performing simple threshold logic. The brain is a network of neurons and this is considered as the first model of connectionism. Furthermore, the McCulloch tradition in Cybernetics led to the development of second order cybernetics. Thus, cybernetics has influenced control theory, computer science, information theory, cognitive science, and artificial intelligence. These studies have formed the basis of autonomous or intelligent systems.

Various methodologies concerning artificial intelligence (AI) have been developed in order to describe and build intelligent agents that perceive an environment, make appropriate decisions, and take actions. In a classical point of view, an intelligent agent was designed based on symbolic representation and manipulation of explicit knowledge. Especially, classical AI has dealt with symbolic search, pattern recognition, and planning. Recently, human intelligence and life itself have been discussed in cognitive science, soft computing, artificial life, and computational intelligence. Soft computing, which was proposed by Zadeh, is a new concept for information processing, and its objective is to realize a new approach for analyzing and creating flexible information processing of human being such as sensing, understanding, learning, recognizing and thinking. Artificial life (A-life) means 'life made by humans rather than nature.' A-life includes three types of approaches: 1) wetware system from the molecular level, 2) software system from the cellular level and 3) hardware system from the organism level. Bezdek discussed intelligence from three levels: artificial, biological, and computational. In the strictest sense, CI depends on numerical data and does not rely on explicit knowledge. Furthermore, Eberhart defined CI as a methodology involving computing. We also summarized CI as follows. CI aims to construct intelligence from the viewpoints of biology, evolution, and self-organization. CI tries to construct intelligence by the bottom-up approach using internal description, while classical AI tries to construct intelligence by the top-down approach using external (explicit) description. However, these research fields use neural computing, fuzzy computing, and evolutionary computing as intelligent techniques. Neural computing and fuzzy computing are based on the mechanism of human brain. While neural computing simulates physiological features of human brain, fuzzy computing simulates psychological features of human brain. Each technique is not complete for realizing all features of intelligence, and therefore, hybridized or combined methods have been proposed for building intelligent systems.

On the other hand, various robots have been developed for human assistance, welfare, amusement, and others. The term of robotics refers to the study and use of robots. Michael Brady defines robotics is the intelligent connection of perception to action. Here a robot, which can acquire and apply knowledge or skill, is called intelligent. Many methodologies have been applied for intelligent capabilities such as learning, reasoning, predicting, communicating, and decision making. Particularly, world modeling, problem solving, and task planning (see *Trajectory and Task Planning*) have been discussed mainly in classical AI, but representative and inferential frame problems and symbol grounding problems have been addressed. To avoid the difficulty in modeling of real world, subsumption architecture was proposed as a new methodology by Brooks. In the subsumption architecture, a robotic behavior is described directly as a coupling of sensory inputs and action outputs without generating its complete world model. The agent design is decomposed into objective-based behaviors such as obstacle avoiding, photo tracing, and map building. This is called behavior-based robotics. Basically, behaviors are designed using finite state machines, but neural networks and fuzzy systems have also been used for describing behavior rules. Furthermore, evolutionary optimization methods and reinforcement learning methods have been applied to robots as methods for acquiring behavior rules through the interaction with environment. In this way, behavior-based robotics and evolutionary robotics have been developed using fuzzy computing, neural computing, evolutionary computing, reinforcement learning, and others.

This section mainly focuses on behavior acquisition of robots using intelligent techniques in unknown environment, because it is very difficult to present all methodologies of intelligent techniques. In the following, we present fuzzy computing, neural computing, evolutionary computing, and reinforcement learning, and finally, discuss intelligence on robotics.

2. Fuzzy Computing

Human beings can deal easily with incomplete and imprecise information. Fuzzy set theory provides us the linguistic representation such as ‘slow’ and ‘fast’. Fuzzy logic expresses a degree of truth, which is represented as a grade of a membership function, while crisp logic such as binary logic deals with true or false, 0 or 1. Figures 1 and 2 show triangular and Gaussian membership functions. A fuzzy inference system derives conclusions from a set of fuzzy if-then rules. The widely used fuzzy inference systems are Mamdani fuzzy models and Takagi-Sugeno fuzzy models, which are also used as fuzzy controllers.

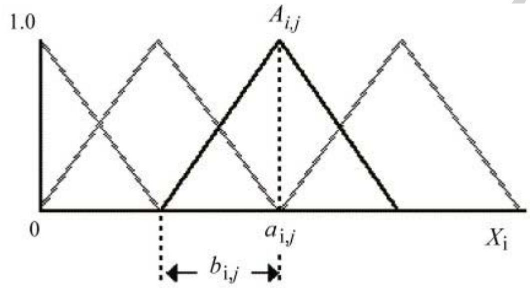

Figure 1: Triangular membership functions

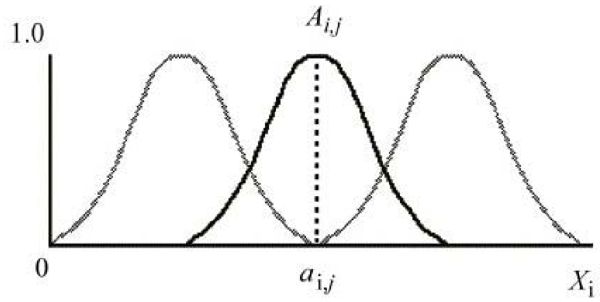

Figure 2: Gaussian membership functions

The feature of the fuzzy controller is the locality of control and the interpolation among local control laws. We present below the fuzzy control and its inference methods.

2.1. Fuzzy Control

Fuzzy control does not explicitly need mathematical models for the controlled system, while classical control theory needs mathematical model expressing the relationship in the controlled system. When the controlled system is more complicated, the mathematical modeling also becomes more difficult. The fuzzy controller enables the control by linguistic representation based on the human expert knowledge.

The fuzzy controller is composed of four main parts: fuzzification, rule-base, inference mechanism, and defuzzification. The fuzzification is the knowledge representation including quantification of input space as a fuzzy set, that is, mapping from a crisp input space to fuzzy sets represented as membership functions. The logical structure written by fuzzy rules is easy for humans to understand and to design. In general, the fuzzy if-then rule for a multi-input multi-output system is described as follows,

if x_1 is $A_{i,1}$ and x_2 is $A_{i,2}$ and ... and x_n is $A_{i,n}$
then y_1 is $B_{i,1}$, and y_2 is $B_{i,2}$ and … and y_o is $B_{i,o}$

where x_j and y_k are variables for the *j*th input and the *k*th output, $A_{i,j}$ and $B_{i,k}$ are membership functions for the *j*th input and the *k*th output of the *i*th rule, and *n* and *o* are the numbers of inputs and outputs, respectively. The commonly used linguistic variables in the fuzzy controller are state variables, state error, differential and integral of state error, and others. Furthermore, the consequence is often described as a singleton or function.

The inference mechanism derives a resulting output from fuzzy if-then rules using crisp input values. When the consequences of fuzzy rules are fuzzy sets, the resulting output also becomes a fuzzy set. Since we need crisp output values for the control, the resulting output as a fuzzy set must be translated into a crisp output value. The defuzzification is used for this translation. Various inference mechanisms and defuzzification methods have been proposed so far. Below we present inference methods and defuzzification methods for fuzzy controller.

2.2. Mamdani Fuzzy Models

The min-max-gravity method, which was proposed by Mamdani, is widely used in various control systems. We show an inference procedure of the min-max-gravity method where x_1 and x_2 are input variables and *y* is an output variable (Figure 3). We present below the procedure of the min-max-gravity method when two crisp inputs x_1^* and x_2^* are given. First, we calculate the membership degrees of $\mu_{A_{i,1}}(x_1^*)$ and $\mu_{A_{i,2}}(x_2^*)$ of the *i*th rule $(i=1,2)$. Next, we calculate the resulting consequence using min operator in the following,

$$\mu_{Bi*}(y) = (\mu_{A_{i,1}}(x_1^*) \wedge \mu_{A_{i,2}}(x_2^*)) \wedge \mu_{Bi}(y). \tag{1}$$

Next, we calculate the resulting output using max operator in the following,

$$\mu_{B^*}(y) = \mu_{B_1^*}(y) \vee \mu_{B_2^*}(y). \tag{2}$$

Finally, we calculate the center of gravity of the fuzzy set $B*(y)$,

$$y* = \frac{\int B*(y)\, y\, dy}{\int B*(y)\, dy} \tag{3}$$

The crisp output y^* is calculated by the above defuzzification.

This defuzzification method is called center of gravity (COG). Furthermore, various defuzzification methods have been proposed such as max criterion method, bisector of area (BOA), mean of maximum (MOM), smallest of maximum (SOM) and largest of maximum (LOM).

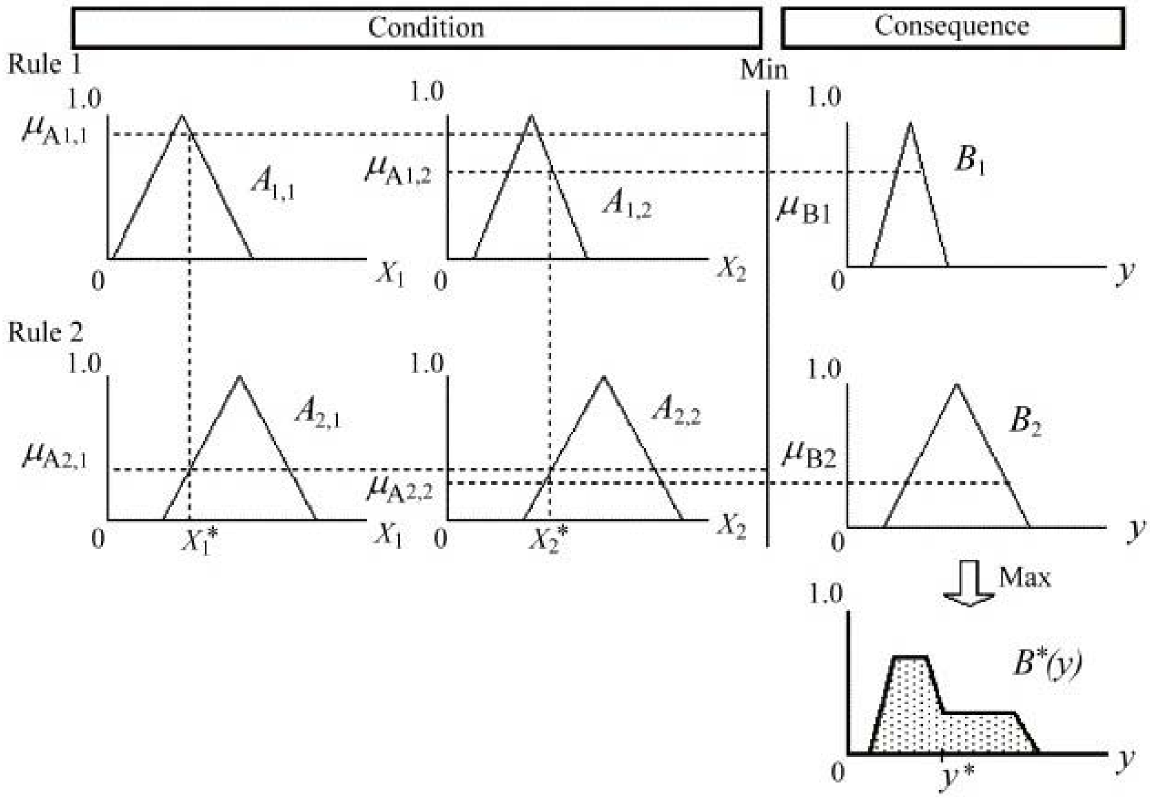

Figure 3: An inference procedure of min-max gravity method

Furthermore, the product-sum-gravity method is often used for fuzzy inference. In the product-sum-gravity method, min and max operators of the min-max-gravity method are replaced with product and sum operators.

We show an inference procedure of the product-sum-gravity method (Fig.4). The product for T-norm operator and the sum for T-conorm operator are performed in the following,

$$\mu_{B_i^*}(y) = \mu_{A_{i,1}}(x_1^*) \times \mu_{A_{i,2}}(x_2^*) \times \mu_{B_i}(y). \tag{4}$$

$$\mu_{B^*}(y) = \mu_{B_1^*}(y) + \mu_{B_2^*}(y). \tag{5}$$

The center of gravity of the fuzzy set $\mu_{B^*}(y)$ using Eq. (3) is calculated.

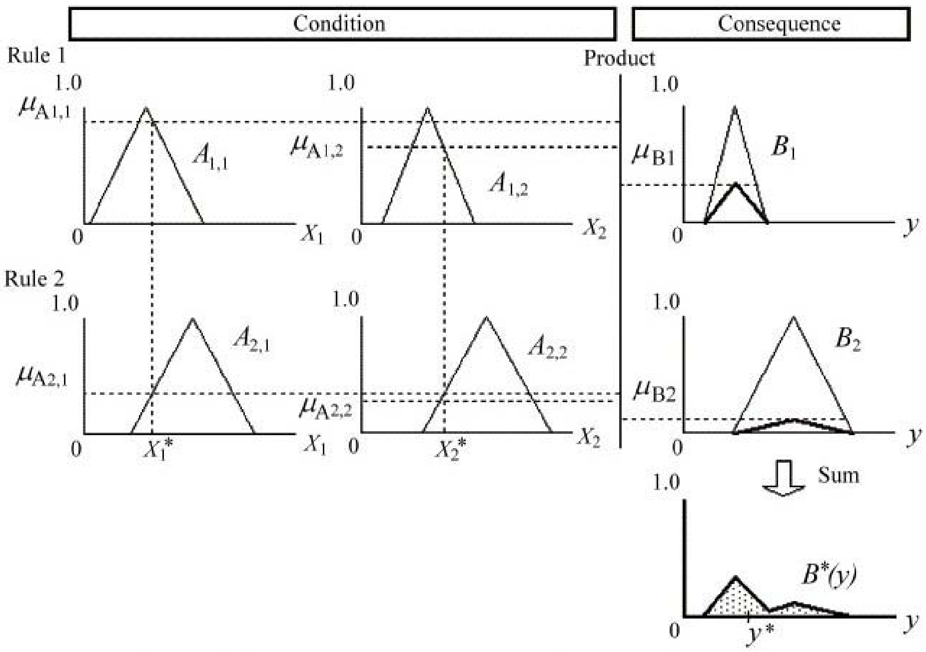

Figure 4: An inference procedure of the product-sum-gravity method

2.3. Functional Fuzzy Inference Methods

The functional fuzzy inference method called Sugeno fuzzy model or TSK Fuzzy model, uses a function in consequence parts. A polynomial function is often used for simplifying the consequence. In general, a fuzzy if-then rule using the functional fuzzy inference method for multi-input single-output system is described as follows,

if x_1 is $A_{i,1}$ and x_2 is $A_{i,2}$ and ... and x_n is $A_{i,n}$ **then** y is $f_i(x_1,\cdots,x_n)$

where $A_{i,j}$ is a membership function for the *j*th input of the *i*th rule, and $f_i(x_1,\cdots,x_n)$ is a function for the output of the *i*th rule. The commonly used function is as follows,

$$f_i(x_1,\cdots,x_n) = a_0 + a_1x_1 + \cdots + a_nx_n \tag{6}$$

where a_0, a_1, $\cdots$, and a_n are coefficients. We show below an inference procedure of the functional fuzzy inference method. First, we calculate the membership degrees of $\mu_{A_{i,j}}(x_j^*)$ of the *j*th input of the *i*th rule $(i=1,2,\cdots,r)$. Next, we calculate the firing strength of the *i*-th rule by product,

$$\mu_i = \prod_{j=1}^{n} \mu_{A_{i,j}}(x_j^*) \tag{7}$$

Finally, the resulting output is calculated using weighted average based on the firing strength,

$$y^* = \frac{\sum_{i=1}^{r} \mu_i f_i(x_1, \cdots, x_n)}{\sum_{i=1}^{r} \mu_i} \tag{8}$$

This method is regarded as a special case of the product-sum-gravity method. Moreover, the min operator can be also used instead of product.

2.4. Simplified Fuzzy Inference Methods

Both min-max-gravity method and product-sum-gravity method use fuzzy sets in the consequences, but the calculation of the gravity takes much computational time. Therefore, the simplified fuzzy inference method has been proposed to reduce computational time. The simplified fuzzy inference method uses a singleton instead of a fuzzy set in the consequence. In general, a fuzzy if-then rule using the simplified fuzzy inference method for a multi-input multi-output system is described as follows,

if x_1 is $A_{i,1}$ and x_2 is $A_{i,2}$ and ... and x_n is $A_{i,n}$
then y_1 is $w_{i,1}$, and y_2 is $w_{i,2}$ and $\cdots$ and y_o is $w_{i,o}$

where x_j and y_k are variables for the *j*th input and the *k*th output $(j = 1, \cdots, n;\ k = 1, \cdots, o)$; $A_{i,j}$ is a membership function for the *j*th input; and $w_{i,k}$ is a singleton for the *k*th output of the *i*th rule $(i = 1, \cdots, r)$, respectively. This method can be regarded as a special case of the functional fuzzy inference method when the consequence is a constant in the functional fuzzy inference method. The resulting output is calculated by the weighted average based on the firing strength,

$$y^* = \frac{\sum_{i=1}^{r} \mu_i \cdot w_i}{\sum_{i=1}^{r} \mu_i} \tag{9}$$

2.5. Learning of Fuzzy If-Then Rules

The linguistic information processing enables the easy inheritance of knowledge among people. Especially, symbolic information processing is easy to logically understand. The rule-base for fuzzy controller can be designed by using human expert knowledge, operator’s control actions, fuzzy modeling, and learning based on experience. The design of rule-base by expert knowledge takes much time, and therefore, the fuzzy controller needs a learning mechanism. Below we show a learning algorithm of the simplified fuzzy inference method for a multi-input single-output system, because this inference method is the simplest one.

When a set of the input-output data is given, the simplified fuzzy inference system can be trained by the generalized delta rule. One can use various types of membership functions such as triangular membership functions, trapezoidal membership functions, and Gaussian membership functions. Here, we consider a triangular membership function (Fig.1). A triangular membership function is generally described as,

$$\mu_{A_{i,j}}(x_j)=\begin{cases}1-\dfrac{\left|x_j-a_{i,j}\right|}{b_{i,j}} & , \quad \left|x_j-a_{i,j}\right|\le b_{i,j}\\ 0 & \quad \text{otherwise}\end{cases} \tag{10}$$

where $a_{i,j}$ and $b_{i,j}$ are the central value and the width of the membership function $A_{i,j}$ (see Figure 1). Consequently, the firing strength is calculated by

$$\mu_i=\prod_{j=1}^{n}\mu_{A_{i,j}}(x_j)=\prod_{j=1}^{n}\left(1-\frac{\left|a_{i,j}-x_j\right|}{b_i}\right) \tag{11}$$

By using equation (9), we obtain the resulting output.

When $Y_{p,k}$ is the kth target output of the controlled system for pattern p, the error function is defined as,

$$E=\sum_{p=1}^{P}E_p$$

$$E=\frac{1}{2}(y^*-y)^2 \tag{12}$$

where P is the number of patterns. To obtain well-worked fuzzy if-then rules, we must minimize the above error function E. When the condition parts (membership functions) are fixed, we can easily train the kth singleton $w_{h,k}$ of the hth rule according to the generalized delta rule based on the error function. The partial derivative of E with respect to $w_{h,k}$ is as follows,

$$\frac{\partial E}{\partial w_k}=\frac{\partial E}{\partial y}\frac{\partial y}{\partial w_k}=-\left(y^*-\frac{\sum\mu_i\cdot w_i}{\sum\mu_i}\right)\frac{\mu_k}{\sum\mu_i} \tag{13}$$

Consequently, we can update the singleton of the consequence of the hth rule by,

$$\begin{aligned}w_k(t+1)&=w_k(t)-\tau\cdot\frac{\partial E}{\partial w_k}\\ &=w_k(t)+\tau\cdot\left(y^*-\frac{\sum\mu_i\cdot w_i}{\sum\mu_i}\right)\frac{\mu_k}{\sum\mu_i}\end{aligned} \tag{14}$$

where η is the learning rate satisfying $0<\eta<1.0$, and t is the learning iteration times.

In any types of membership functions, the singletons of fuzzy rules can be trained by the generalized delta rule, since the output depends on the firing strength of each rule based on the grade of the membership function where the crisp input values are given.

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Biographical Sketches

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Toshio Fukuda graduated from Waseda University in 1971 and received the Master of Engineering degree and Dr. Eng. from the University of Tokyo in 1973 and 1977, respectively. Meanwhile, he studied at the graduate school of Yale University from 1973 to 1975. In 1977, he joined the National Mechanical Engineering Laboratory and became Visiting Research Fellow at the University of Stuttgart from 1979 to 1980. He joined the Science University of Tokyo in 1982, and then joined Nagoya University in 1989. Currently, he is Professor of Department of Micro System Engineering and Department of Mechano-Informatics and Systems, Nagoya University, Japan, mainly engaging in the research fields of intelligent robotic system, cellular robotic system, mechatronics and micro robotics. He is an author of six books, editing five books and has published over 1,000 technical papers in micro system, robotics, mechatronics and automation areas. He was awarded IEEE Fellow, SICE Fellow (1995), IEEE Eugene Mittlemann Award (1997), Banki Donat Medal form Polytechnic University of Budapest, Hungary (1997), Medal from City of Sartillo, Mexico (1998), IEEE Millennium Medal (2000) and JSME Fellow (2001). He is the Vice President of IEEE IES (1990 - 1999), IEEE Neural Network Council Secretary (1992 -1993), IFSA Vice President (1997 -), IEEE Robotics and Automation Society President (1998 - 1999), current Editor-in-Chief, IEEE / ASME Transactions on Mechatronics (2000 -), current IEEE Division X Director (2001-), and current IEEE Nanotechnology Council President (2002-).