ソフトコンピューティングによる知的制御

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Intelligent Control Using Soft Computing

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Firstly, intelligent control (diagnosis by system identification) for a small-scaled system using computational intelligence (soft computing and numerical processing) is described. A novel fuzzy neural network with general parameter learning is developed, which needs remarkably less computational time resulting in realizing real time fault detection of an automobile transmission gear with a DSP-integrated RISC processor. Then, for a large-scaled and complex system, contemporary intelligent control using extended soft computing is proposed. Extended soft computing (ESC) which is the fusion/combination of fuzzy, neuro, genetic and chaotic computings and immune network theory in order to explain, what they call, complex systems and cognitive and reactive AIs is introduced. Then, contemporary intelligent system concept is discussed while the ESC is promising to realize it. Finally, a decision making robot with multi-agents (immune networks), fuzzy inference and reinforcement learning is described, as an example. It is confirmed that the ESC plays an important role in constructing intelligent robots.

Keywords: Computational Intelligence, Soft Computing, Intelligent Control, Fuzzy System, Neural Network, Immune Network

1 INTRODUCTION

Soft computing is proposed by Dr. L.A.Zadeh[1][2][3] to construct new generation AI (machine intelligence quatient) and to solve nonlinear and mathematically un-modelled systems problems (tractability). It is the fusion or combination of fuzzy, neuro and evolutional (genetic algorithm) computings. The advantages of soft computing (computational intelligence) for control and diagnosis of systems are

1. Nonlinear and comblicated problems, problems for which mathematical models are defficult to obtain.
2. Human knowledge (recognition, understanding, learning, inference and other human intelligence) can be introduced. Therefore intelligent systems such as autonomous (self-organizing controllers), self-tuning systems and automated designed systems can be constructed.

Now, only the combination of fuzzy systems and neural networks are considered. It has been proved that any nonlinear mappings obtained by neural networks can be approximated, to any accuracy, by fuzzy systems using Stone-Weierstrass's approximation theory[4]. From the application point of view, each approach has some advantages. Since a neural

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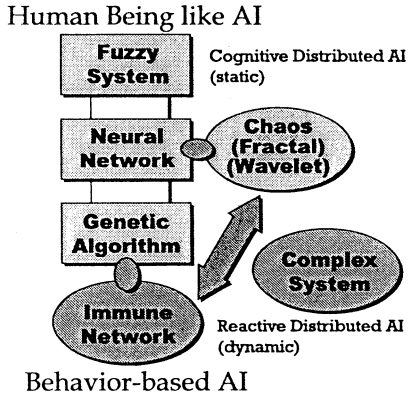

Fig. 1. Soft computing in AI

network has learning capabilities, it is easy to design automatically controllers.

On the other hand, for fine-tuning, in using neural networks, it is difficult, since it is difficult to explain logically the cause and the result in the input-output relation ships. Due to these difficulties, a novel local based function neural network with a general parameter learning algorithm was developed[5]. It is experimentally applied to fault detection of automobile transmission gears by nonlinear system identification in Section 2.

Then, in Section 3 by adding chaos computing and immune network theory, extended soft computing (ESC) is defined for explaining, what they call, complex systems and cognitive and reactive AIs as shown in Fig.1. In Section 4, contemporary intelligent control for a large-scaled and complex system is considered from the view point of bioinformatics and cognitive and reactive distributed AIs while the ESC is promising to realize it. Especially, cognitive and reactive distributed artificial AIs are discussed.

In Section 5, control of an intelligent agent robot is described. Robots can behave more intellectually in a group even though each robot has a little intelligence, since they can interact in cooperation with each other. The following methods using soft computing to construct intelligent multi agent robot systems have been reported.

1. Immune networks, fuzzy inference and GA (reactive distributed AI, IFAR)[6][7]
2. Neural networks and evolutional computing (reactive and cognitive distributed AI)(perception and motion are non separable, IFAR)[8]
3. Fuzzy associate memories, chaos computings and evolutional computoings (cognitive distributed AI)(each agent has intelligence in this case, IFAR)[9]
4. Fuzzy inference and random parameter search method (reactive distributed AI, MAIR)[10][11]

An artificial decision making robot behaving as interactions(fuzzy inferences) among antibodies in an artificial immune network with perceptions of antigens is described. It is confirmed that the ESC is promising to realize intelligent agent robots like this.

2 REAL TIME FAULT DIAGNOSIS

2.1 Nonlinear Model Identification

A necessary basis for any diagnostics approach is a reliable and accurate model of the operational process. Therefore, fault detection/diagnostics procedures typically consist of the following two steps:

1. Off-line determination of the model structure and its parameters under normal operation conditions.
2. On-line determination of operational faults by using the identified model.

We use the GP-approach for both of the above steps. The nonlinear time-series model is first expressed as:

$$x(n) = F[x(n-1), \cdots, x(n-N)] + \eta(n) \quad (1)$$

where $F[\cdot]$ is a nonlinear function and $\eta(n)$ represents the modeling error.

In the identification stage, the general parameter (β) expectation and variance are indicators of the current accuracy of the normal process model. In the diagnostics stage, the mentioned values are indicators of process normality. The GP-based model identification procedure is described below

1. Model initialization:

$$\hat{w}_i(0) = 0; \quad \beta(0) = 0$$
$$E\{\beta\} = 0; \quad D_\beta = 0$$

2. Sample $x(k), k \in [1, N]$
3. Caluculate the one-step-ahead predictive GP-RBFN output $\hat{x}(k+1)$
4. Sample $x(k+1)$
5. Adapt β with the algorithm[5]
6. Compute general parameter's expectation $E\{\beta(k)\}$ and variance $D_\beta(k)$
7. Determine expectation's and variance's possible stability:

$$\Delta E\{\beta\} = |E\{\beta(k+1)\} - E\{\beta(k)\}| < \delta_1$$
$$\Delta D_\beta = |D_\beta(k+1) - D_\beta(k)| < \delta_2$$

where, δ_1, δ_2 are appropriate threshold levels.

8. If stability is achieved in Step 7, then go to Step 10, else continue.
9. $k = k + 1$, go to Step 3.

10. $\hat{w}_i = E\{\beta(k)\}$

11. $k = k + 1$

12. Caluculate the new GP-RBFN output.

13. Sample $x(k+1)$

14. Accuracy justification:

$$\begin{aligned} \epsilon(k+1) &= x(k+1) - \hat{x}(k+1) \\ D_\epsilon(k+1) &= \frac{k}{k+1} D_\epsilon(k) + \frac{k}{k+1} \epsilon^2(k+1) \end{aligned}$$

15. If $D_\epsilon < \delta_\epsilon = const > 0$, then go to Step 18, else continue.

16. Individual adaptation of RBFN weights.

17. Go to Step 11.

18. Memorizing of the new weight values $\hat{w}_{i0} = \hat{w}_i(k)$.

19. Zeroing of the general parameter value $\beta = 0$.

2.2 Process Abnormality Detection

After identifying the model structure and its parameters of the plant for normal operation conditions, the fault detection problem can be solved using the following procedure: η

1. Initialization:

$$\hat{w}_i(0) = \hat{w}_{i0} = const$$
$$\beta(0) = 0; E\{\beta\} = 0; D_\beta = 0$$

2. Sample $x(k), k \in [1, N]$.

3. Calculate GP-RBFN output.

4. Sample $x(k+1)$.

5. Adapt β with the algorithm[2].

6. Estimate the general parameter expection $E\{\beta(k)\}$ and variance $D_\beta(k)$.

7. Justification of operation normality: $|E\{\beta(k)\}| < \Delta_1, D_\beta(k) < \Delta_2$, where $\Delta_1, \Delta_2 = const > 0$ are predetermined threshold values.

8. If the conditions of Step 7 are not satisfied, then fault is detected, else continue.

9. $k = k + 1$, go to Step 3.

2.3 Fault Detection Experiment

We consider a fault detection problem of automobile transmission gears by means of acoustic data modeling. The input data was collected using a sound level meter. First, the normal model was identified by the conventional RBFN and then by the new GP-RBFN (fuzzy neural network). Both networks were trained off-line. Fig. 3 illustrates the approximation errors of the RBFN and GP-RBFN after an equal number of training steps. It is seen from these plots that the prediction error is significantly lower and more consistent with the GP-RBFN. This is due to the considerably faster learning rate of the GP-RBFN.

During the on-line fault detection stage, the regular weights of the GP-RBFN were fixed, while the scalar general parameter was adapted. In Fig. 4, illustrative results are shown, where the general parameter expectation value allows to easily recognize an abnormal condition in the automobile transmission system. This experiment was carried out using the following parameters (Fig. 2): the number of delay elements was 10, the number of Gaussian functions was 7, and the width of each Gaussian function from the center was 0.2.

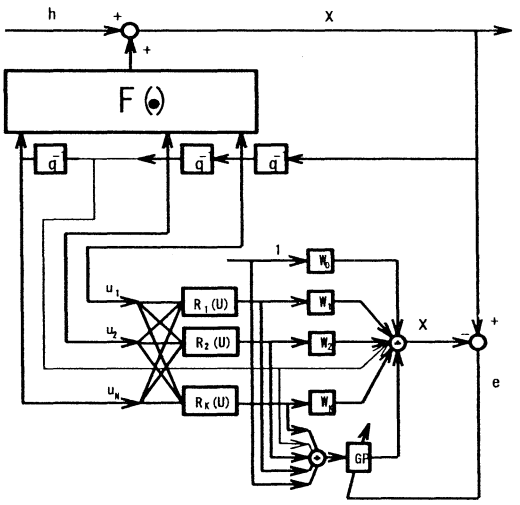

Fig. 2. Nonlinear time series identification system

3 EXTENDED SOFT COMPUTING

Soft computing is proposed by Dr. L.A.Zadeh[1][2][3] to construct new generation AI (machine intelligence quatient) and to solve nonlinear and mathematically unmodelled systems problems (tractability) especially for cognitive artificial intelligence by adding chaos computing and immune network theory.

Extended soft computing is defined for explaining, what they call, complex systems, cognitive and

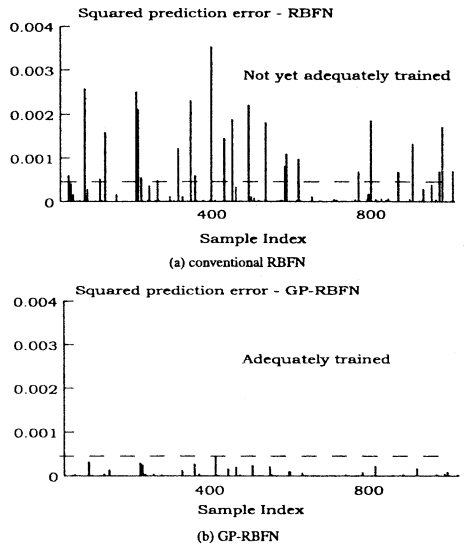

Fig. 3. Prediction with RBFN

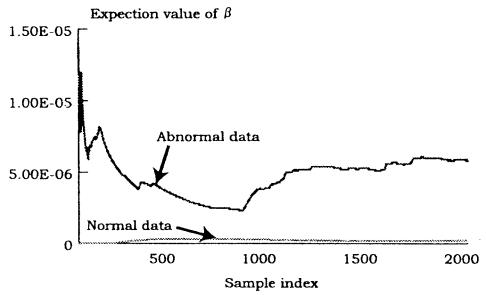

Fig. 4. Fault detection with general parameter

reactive AIs. Immune networks are promising approaches to construct reactive artificial intelligence and as illustrated in Fig.1. Industrial and commercial applications of NN/FS/GA/Chaos in 1990s is discussed in [12][13].

3.1 Reactive Distributed AI

Reactivity is a behavior-based model of activity, as opposed to the symbol manipulation model used in planning. This leads to the notion of cognitive cost, i.e., the complexity of the over architecture needed to achieve a task.

Cognitive agents support a complex architecture which means that their cognitive cost is high. Cognitive agents have internal representation of the world which must be in adequation with the world itself. The process of relating the internal representation and the world is considered as a complex task.

On the other hand, reactive agents are simple, easy to understand and do not support internal representation of the world. Thus, their cognitive cost is low, and tend to what is called cognitive economy, the property of being able to perform even complex actions with simple architectures. Because of their complexity, cognitive agents are often considered as self-sufficient: they can work alone or with a few other agents.

On the contrary, reactive agents need companionship. They can not work isolated and they usually achieve their tasks in groups. Reactive agents can not work isolated and they usually achieve their tasks in groups. Reactive agents do not take past events into account, and can not foresee the future. Their action is based on what happens now, how they sense distinguish situations in the world, on the way they recognize world indexes and react accordingly.

Thus, reactive agents cannot plan ahead what they will do. But, what can be considered as a weakness is one of their strengths because they do not have to revise their world model when perturbations change the world in an unexpected way. Robustness and fault tolerance are two of the main properties of reactive agent systems. A group of reactive agents can complete tasks even when one of them breaks down. The loss of one agent does not prohibit the completion of the whole task, because allocation of roles is achieved locally by perception of the environmental needs. Thus, reactive agent systems are considered as very flexible and adaptive [14].

4 CONTEMPORARY INTELLIGENT SYSTEMS

This section introduces contemporary intelligent systems using the extended soft computing described in the previous section and bioinformatic knowledge.

It is interactive among human beings, environment and artificial intelligence. The relations among each method of the extended soft computing are important rather than the methods themselves. It should be self-organized emergent intelligence rather than embeded by a designer. It is emergent, self-organized and reflective in each granularity level like bioiformatic processing. Learning should be embeded by situated cognition and situated action. Perception and motion are not separable[15][16]. This is illustrated in Fig.5.

To explain this, bioinformatic cybernetic is compared with conventional cybernetics in Table 1.

Table 1. Comparison of conventional and bioinformatics cybernetics

Conventional cybernetic	Bioinformatic
Expicit (Object & observation are separated)	Implicit (perception & motion are not separated)
Homeostasis (stability)	Diversity
Topdown	Bottomup
Close system (feedback)	Open (feedforward)
Determinstic	Emergent
Optimization (product)	Adaptive learning
	Evolution (process)

Learning is achieved as shown in Fig.6 and Fig7. Human beings is sometimes in intelligent systems[17].
Kansei information processing is now popular in Japan.

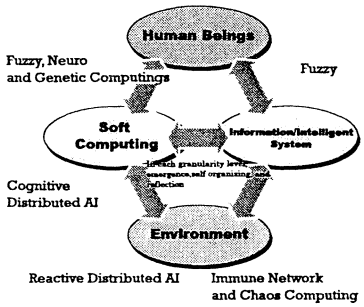

Fig. 5. Contemporary intelligent system concept

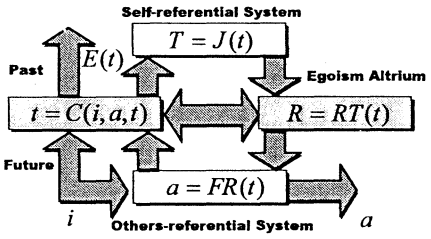

Fig. 6. Bi-referential model

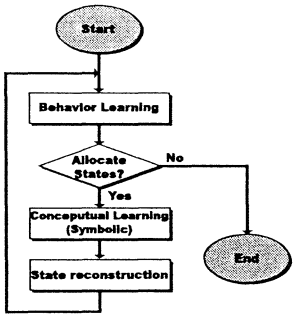

Fig. 7. Learning algorithm

5 DESISION MAKING ROBOT WITH MULTI-AGENTS (ANTIBODY) AND PERCEPTION (ANTIGENS) IN IMMUNE NETWORK USING FUZZY INFERENCE AND REINFORCEMENT LEARNING[18]

'immunoid' by interactions among antibodies in artificial immune networks is considered. In this simulated environment, there are following three k

An artificial decision making robot inds of objects: 1)predator 2) obstacles 3) food. It is assumed that prespecified quantity of initial energy is given to the immunoid at the beginning of each simulation. For quantitative evaluation, the following assumptions are made.

1. If the immunoid moves, it comsumes energy E_m.
2. If the immunoid is captured by a predator, it comsumes energy E_p.
3. If the immunoid collides with an obstacle, it losses energy E_o.
4. If the immunoid picks up food once, it obtains energy E_I.

The predators attack the immunoid if they detect the immunoid within the prespecified detectable range. Therefore, in order to survive as long as possible, the immunoid must select a competence module (antidody) suitable for the current situation(antigen). The immunoid equipped with external and internal detectors. External detectors can sense eight directions as shown in Fig.8.

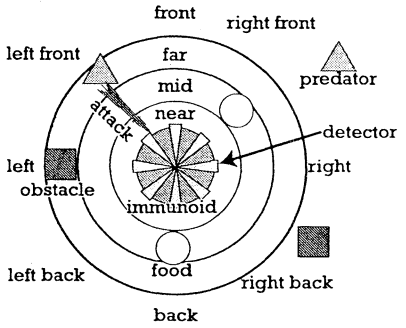

Fig. 8. Simulated environment

Each can detect the distance to the objects by three degrees, near, mid and far. The internal detector senses the current energy level. The immunoide moves in his eight directions.

The detected current situation and prepared competence modules work as antigens and antibodies, respectively. To make a imunoido (antibody) select a suitable antibody against the current antigen. It is highly important how the antibodies are described. Moreover, it is noticed that the immunogical arbitration mechanism selects an antibody in bottom up manner by communicating among the antibodies. To realize the above requirements, the description of antibodies are defined as follows. The identity of a specific antibody is generally determined by the structure of its paratope and idiotope.

As shown in this Fig. 9, a pair of precondition action to paratope, the number of disallowed antibodies and the degree of disallowance to idiotope

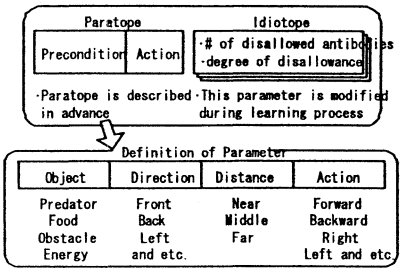

Fig. 9. Depicts the representation of antibodies.

are respectively assigned. In addition, the structure of paratope is divided into four portions: objects, direction, distance, and action.

For adequate selection of antibodies, one state variable called concentration is assigned to each antibody. The selection of antibodies is simply carried out in a winner-take all fashion. Namely, only one antibody is allowed to activate and act its corresponding its action to the world if its concentration surpasses the prespecified threshhold. The concentration of the antibody is influenced by the stimulation and suppression from other antibodies, the stimulation from antigen, and the dissipation factor (i.e. natural death). The concentration of *i-th* antibody, which is denoted by a_i, is calculated by eq(2). α and β are the rate of interaction among antigens and antibodies.

$$\frac{dA_i(t)}{dt} = \left(\alpha \frac{\sum_{j=1}^{N} m_{ji} a_j(t)}{\sum_{j=1}^{N} m_{ji}} - \alpha \frac{\sum_{k=1}^{N} m_{ik} a_k(t)}{\sum_{k=1}^{N} m_{ik}} + \beta m_i - k_i \right) a_i(t) \quad (2)$$

$$a_i(t+1) = \frac{1}{1+\exp(0.5 - A_i(t))} \cdots\cdots (3)$$

where N is the number of antibodies, and m_i denotes matching ratio between antibody i and antigen, m_{ij}, that denotes degree of disallowance of antibody j for anti-body i. The first and second terms of right hand sidedenote the stimulation and suppression from other antibodies, respectively. The third term represents the stimulation from antigen, and the forth term the natural death.

Simulation results:
100 simulations are carried out with # of predators: 5, # of obstacles:5, # of foods: 10, and # of antibodies:91.

Average life time:
A. Immunoid's random walk: 313.14
B. Without interactions among antibodies: 564.86
C. With interactions among antibodies: 621.46

Table 2. # of collides against predators and obstacles and obtaining foods:

	predators	obstacles	foods
A	19.91	1.84	0.54
B	9.04	5.92	4.27
C	7.84	5.23	5.02

This approach is promising for decision making in autonomous mobile robots (one of multi-agent robots). However, two disadvantages exist. One is how to cope with environment changes, and the other is how to design agents. It is required in the future to devise some real time reinforcement learning.

6 CONCLUSIONS

This paper proposes a comtemporary intelligent multi-agent robot using extended soft computing.

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REFERENCES

(1) L. A. Zadeh, "Fuzzy Logic and Soft computing", Plenary Speaker, Proc. Of the IEEE Int. Workshop on Neuro Fuzzy Control, Muroran Japan, Mar.22-23, 1993.

(2) L. A. Zadeh, "The Role of Soft Computing and Fuzzy Logic in the Conception, Design, Devlopment of Intelligent Systems ", Plenary Speaker, Proc. of the Int. Workshop on Soft Computing Industry, Muroan Japan, Apr.27-28, 1996.

(3) L. A. Zadeh, "From Computing with Numbers to Computing with words - from Manipulation of Measurements to Manupilation of Perceptions", Plenary Speaker, Proc. of the IEEE Int. Workshop on Soft Computing in Industry, Muroran, Japan, June 16-18, 1999.

(4) L. X. Wang, "Fuzzy Systems are Universal Approximations", Proc. of the IEEE Fuzzy Systems, San Francisco U.S.A.,1992.

(5) D. F. Akhmetov, Y. Dote, Y. Suzuki and S. Saga, "General Parameter Radial Basis Function Based Adaptive Fuzzy Systems" Journal of Fuzzy Systems (JSFS), Nov.1998.

(6) A. Ishiguro, T. Kondo, Y. Watanabe and Y. Uchikawa, "An Immunological Approach to Behavior Control of Autonomous Mobile Robots-

Construction of Immune network Through Learning", Proc. of the IWSCI, Muroran, Japan, April 27-28, 1996

(7) T. Nohara and H. Takahashi, "Automated Trasportation Control System of AGV (Automated Guided Vehicle) Using Artificial Immune Network—Application to Container Terminal", Journal of High Speed Signal Processing Application, Vol.3, No.1, 2000.(in Japanese)

(8) H. Nakamura, A. Ishiguro, Y. Uchikawa and R. Pfeifer, " Exploiting Embodiment to Solve Some of the Hard Classification Problems: Proc. of the Int. Workshop on Signal Processing Applications & Technology, Nagoya, Japan, Oct.1998.

(9) N. Kohata, T. Yamaguchi, M. Takahide, T. Baba and H. Hashimoto, "Dynamic Formation on MobileAgents and Its Evolutionary Parallel Computation", Proc. of the IEEE SMC, Tokyo, Japan, Oct.13-15,1999

(10) K. Hirasawa, J. Misawa and J. Hu, "A Learning Method for Dynamics of Multi-Agent System with Mutual Interaction Based on Fuzzy Inference", Trans. On SICE, Vol35, No.11, 1999(In Japanese)

(11) S. Suzuki, T. Kamano and T. Anno, "Cooperative Multi-Agent Robot for Catching One Target Object", bit, Vol.32, No.4, April Japanese)

(12) H. Takagi, " Indusstrial and Commercial Applications of NN/FS/GA/Chaos in 1990s" Proc. of the IEEE Int. Workshop on Soft Computing in Industry, Muroran, Japan, Apr. 27-28, 1996.

(13) Y. Dote and R. G. Hoft: Chapter 8, Intelligent Control: Power Electronic Systems, Oxford University, 1998.(with Dr.L.A.Zadeh's foreword)

(14) G. M. P. O'Hare and N. R. Jenings: Reactive Distributed Artificial Intelligence, Jhon Wiley & Sons Inc. U.S.A. ,1996

(15) T. Sawaragi, "Post Intelligent Control: Perspectives on on Bioinformatic Control Systems", Proc. of the JIEE meeting on Intelligent Control, Keio University Japan, Sept. 1998.

(16) M. Sasaki: Affordance, Iwanami Shoten Japan, Oct. 1995 (in Japanese)

(17) H. Takagi: Tutorial, "Interactive Evolutionary Computation", The IEEE SMC, San Diego U.S.A., Oct. 1998.

(18) T. Nakane: Decision Making Using Immune Networks, M.S. [Thesis, Muroran Institute of Technology, March 2000 (in Japanese)

ソフトコンピューティングによる知的制御

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概要

最初に、コンピュテーショナルインテリジェンスを用いた小規模システム対する知的制御について記す。ジェネラルパラメータ法によるファジィニューラルネットワークを開発し、計算時間が著しく減少、リアルタイムでの自動車のトランスミッションギアの故障検出を実現している。次に、大規模で複雑なシステムに対しては、拡張されたソフトコンピューティング (ESC) を使った現代の知的制御を提案している。現代の知的制御システムの概念が議論される一方で、ESCが将来有望であることは間違いない。最後に例として、マルチエージェントの意思決定ロボットやそのファジィ推論、強化学習について記している。

キーワード：コンピュテーショナルインテリジェンス、ソフトコンピューティング、知的制御、ファジィシステム、ニューラルネットワーク、免疫ネットワーク

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