Chapter

Overview of Some Intelligent Control Structures and Dedicated Algorithms

Kuo-Chi Chang, Kai-Chun Chu, Yuh-Chung Lin and Jeng-Shyang Pan

Abstract

Automatic control refers to the use of a control device to make the controlled object automatically run or keep the state unchanged without the participation of people. The guiding ideology of intelligent control is based on people's way of thinking and ability to solve problems, in order to solve the current methods that require human intelligence. We already know that the complexity of the controlled object includes model uncertainty, high nonlinearity, distributed sensors/actuators, dynamic mutations, multiple time scales, complex information patterns, big data process, and strict characteristic indicators, etc. In addition, the complexity of the environment manifests itself in uncertainty and uncertainty of change. Based on this, various researches continue to suggest that the main methods of intelligent control can include expert control, fuzzy control, neural network control, hierarchical intelligent control, anthropomorphic intelligent control, integrated intelligent control, combined intelligent control, chaos control, wavelet theory, etc. However, it is difficult to want all the intelligent control methods in a chapter, so this chapter focuses on intelligent control based on fuzzy logic, intelligent control based on neural network, expert control and human-like intelligent control, and hierarchical intelligent control and learning control, and provide relevant and useful programming for readers to practice.

Keywords: artificial intelligence algorithm, adaptive fuzzy control, neural network, expert system, learning control

1. Intelligent control based on fuzzy logic

1.1 Basic knowledge of fuzzy logic

A set of things can be distinguished based on binary logic. The essence of the set concept is to classify or divide things according to certain attributes. The whole of all the elements of the research object is called "universe", which is represented by U, also known as "set", "entire domain" or "space". Eigen functions are an important way to represent classical sets. For fuzzy sets and fuzzy concepts, from the perspective of set theory, the connotation of a concept is the definition of a set, and expansion is all the elements that make up a set. In people's mind, there are many concepts that are not explicitly extended, called fuzzy concepts, such as "high" and "short" to describe height [1].

The general approximation analysis of fuzzy systems is a non-linear mapping from input to output. It consists of multiple "If … Then … " rules. These rules have simple geometric features in the input and output spaces X × Y, and define many fuzzy blocks on the X × Y space. "If X is a fuzzy set A1, then Y is a fuzzy set B1." This rule corresponds to the A1 × B1 Cartesian product of the input and output spaces. The overlapping function f: X → Y of fuzzy blocks composed of fuzzy rules can be used to approximate the function f: X → Y with the fuzzy system F: X → Y.

Summarizing the control behavior of the above-mentioned people is following the basic idea of feedback control. An experienced operator can summarize the principle of manual operation to control the furnace temperature. The accumulated operating experience accumulated over the years can be summarized into several rules, such as "if the furnace temperature is low, add more fuel", etc., to train young operators that he is qualified for the job and gradually replace. Similarly, several control rules summarized from operating experience can be stored in a computer, allowing the computer to imitate human control decision-making behaviors to automatically control the furnace temperature. This is the basic idea of fuzzy control.

1.2 Components of the fuzzy control system

There is not much difference between a fuzzy control system and a computer digital control system. As shown in **Figure 1**, a fuzzy control system can be divided into four components: fuzzy controller, A/D and D/A interface to U, generalized objects (actuators and controlled objects) and sensors [2].

In the microcomputer fuzzy control system, the sensor replaces the human eye, the fuzzy controller replaces the human brain to control decisions, and the executive mechanism replaces the functions of the human arm and hand.

1.2.1 The basic form of fuzzy control

The decision-making process of fuzzy control is the three basic forms of human fuzzy thinking include fuzzy concept, fuzzy judgment and fuzzy reasoning. In the fuzzy controller, the fuzzy concept is a fuzzy linguistic variable represented by a fuzzy set. For example, the exact amount of error (continuous domain) is converted to the fuzzy quantity on the discrete domain (discourse domain). This process is called fuzzy quantization processing.

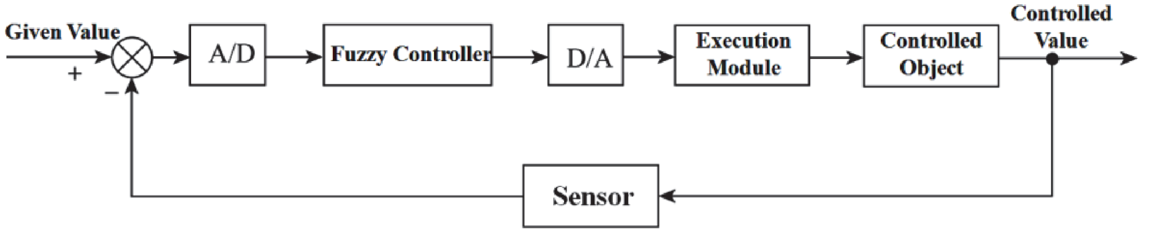

Figure 1.
Block diagram of fuzzy control system.

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Human operating experience can be summarized into several fuzzy control rules in language. These rules can be described by a fuzzy relation matrix. It is actually a general principle of the operating process. These fuzzy control rules are also called the language model of the controlled object.

According to the syllogistic fuzzy reasoning synthesis rule, the fuzzy relationship determined by the fuzzy control rule is taken as the major premise of fuzzy reasoning, and the input fuzzy variable is used as the small premise. The known small premise and fuzzy relationship can be concluded by fuzzy inference synthesis.

According to the syllogism fuzzy inference synthesis rule, the fuzzy relationship $\underline{R}$ determined by the fuzzy control rule is taken as the major premise of fuzzy reasoning, the input fuzzy variable is $\underline{A}$ is taken as the small premise, and the known small premise A and fuzzy relationship R are synthesized by fuzzy relation inference Conclusion $\underline{B} = \underline{A} \circ \underline{R}$.

As shown in **Figure 2**, the schematic diagram of the fuzzy control system is given. For the sake of comparison, the fuzzy logic thinking form of the person is placed above the figure. The three forms of fuzzy logical thinking correspond. Among them, the fuzzy quantization process is to obtain the fuzzy amount of the control variable [3].

For the sake of simplicity, only the error signal is selected as the input variable of the fuzzy controller and abbreviated as e (t) to illustrate the working principle of the fuzzy controller. The microcomputer obtains the precise value of the controlled quantity y by interrupting the sampling, and then compares this quantity with the given quantity to obtain the precise value of the error signal e ($e = r\text{-}y$, here the unit feedback is taken) as the input quantity of the fuzzy controller. The exact amount of the error e becomes the fuzzy amount of the error through the fuzzy quantization process, which can be represented by a subset $\underline{e}$ of the corresponding fuzzy language set. Then the fuzzy relationship between the fuzzy amount of the error $\underline{e}$ and the fuzzy control rule $\underline{R}$ is used to make a fuzzy inference decision. The fuzzy amount of the control amount is shown in Eq. (1).

$$\underline{u} = \underline{e} \circ \underline{R} \tag{1}$$

The fuzzy amount of the control amount cannot be directly sent to the actuator to control the controlled object, the fuzzy amount of $\underline{u}$ of the control amount must

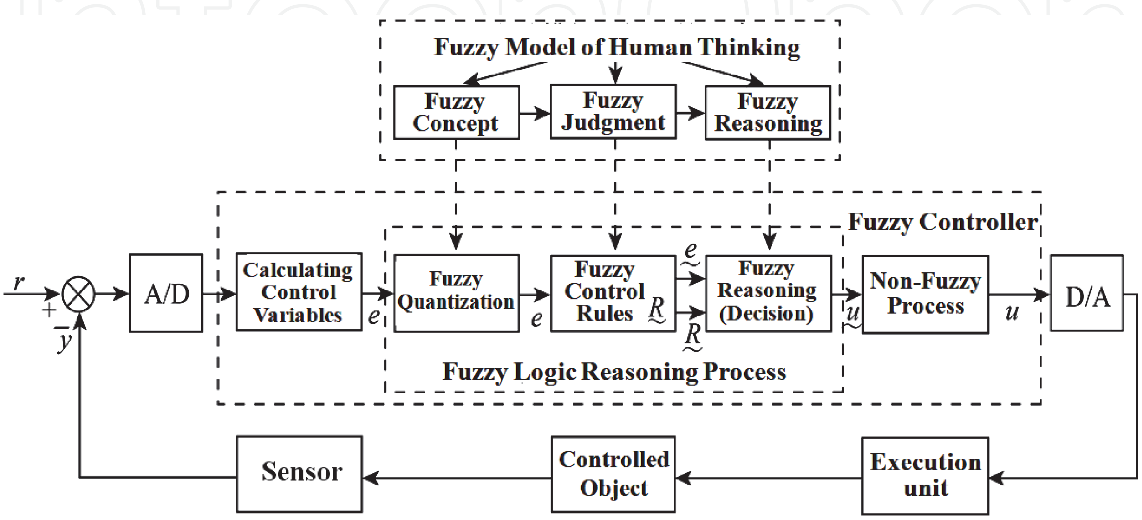

Figure 2.
System principle of fuzzy control.

also be converted into an accurate amount u through non-fuzzy (clarification, deblurring, and defuzzification) processing. After the digital-to-analog conversion into an accurate analog quantity, it is sent to the executive body, which controls the controlled object by one step. Then, it waits for the second sampling and performs the second step control. Continuously controlling in this way will make the actual output of the controlled object approach the expected value with certain accuracy, thereby achieving fuzzy control of the controlled object.

It is not difficult to see that the input quantity e of the fuzzy controller is an accurate quantity, and its output control quantity u is also an accurate quantity. Therefore, the control of the fuzzy controller is not fuzzy, and it can achieve precise control of the controlled object. Only the fuzzy logic reasoning is used in the inference part of the fuzzy controller. The advantages are: first, this reasoning decision does not require an accurate mathematical model of the controlled object; second, this reasoning decision simulates the thinking process of a person, and has intelligent and efficiency.

In the following, a single input single output temperature fuzzy control system is used to specifically explain the working principle of the fuzzy control system. An electric heating furnace is used for the heat treatment of metal parts. According to the requirements of the heat treatment process, the furnace temperature must be kept constant at 600°C. The experience of manual operation to adjust the voltage to control the furnace temperature can be summarized in language as the following control rules: If the furnace temperature is lower than 600°C, the voltage will be increased. When the temperature is lower, the voltage will be higher. If the furnace temperature is equal to 600°C, the voltage will be kept unchanged, as the voltage increases, the voltage will decrease.

According to the above control rules, the application of a microcomputer to achieve fuzzy control of the furnace temperature needs to be designed according to the following steps.

1. Determine the input and output variables of the fuzzy controller.

   Select the difference between the actual value of the furnace temperature and the set value as $e\ (n) = t0\text{-}t\ (n)$ as the error input variable, and select the voltage u to adjust the furnace temperature as the output variable of the fuzzy controller.

2. Determine fuzzy language variables of input and output variables.

   First, select a fuzzy subset of the input and output variables as:

   {Negative large, negative small, zero, positive small, positive large} = {*NB, NS, O, PS, PB*}.

Among them, *NB, NS, O, PS, PB* are English abbreviations of negative large, negative small, zero, positive small, and positive large respectively.

Second, the domain X of the selection error e and the domain Y of the control quantity u are both $X = Y = \{-3, -2, -1, 0, 1, 2, 3\}$.

Third, determine the membership functions of the input and output language variables as shown in **Figure 3**. From this, the assignment of fuzzy variables $\underline{e}$ and $\underline{u}$ can be obtained from this, see **Table 1** [4].

Establish fuzzy control rules using the above-mentioned rules for manually adjusting the voltage to control the furnace temperature, using the error as an input variable, and the voltage as an output variable, five rules can be written as follows:

1. If the error is negative, the voltage is positive; If $\underset{\sim}{e} = NB$ then $\underset{\sim}{u} = PB$.

2. If the error is small, the voltage is small; If $\underset{\sim}{e} = NS$ then $\underset{\sim}{u} = PS$.

3. If the error is zero, then the voltage is zero; If $\underset{\sim}{e} = O$ then $\underset{\sim}{u} = O$.

4. If the error is small, then the voltage is small; If $\underset{\sim}{e} = PS$ then $\underset{\sim}{u} = NS$.

5. If the error is positive, the voltage is negative; If $\underset{\sim}{e} = PB$ then $\underset{\sim}{u} = NB$.

In the above rules, the left side is expressed in Chinese, and the right side is written in English if-then fuzzy conditional statements.

1.2.2 Fuzzy matrix representation of fuzzy control rules

A fuzzy control rule is actually a set of multiple fuzzy conditional statements, which can be expressed as a fuzzy relationship from the error domain X to the control quantity domain Y. Because when the universe is limited, fuzzy relations can be represented by fuzzy matrices. In the furnace temperature fuzzy control, the universe of discussion X and Y are limited to 7 levels, so the fuzzy relation matrix can be used to represent the above fuzzy control rules.

The above fuzzy conditional statement can be expressed as a fuzzy relationship as show in Eq. (2).

$$\underset{\sim}{R} = NB_e \times PB_u + NS_e \times PS_u + O_e \times O_u + PS_e \times NS_u + PB_e \times NB_u \tag{2}$$

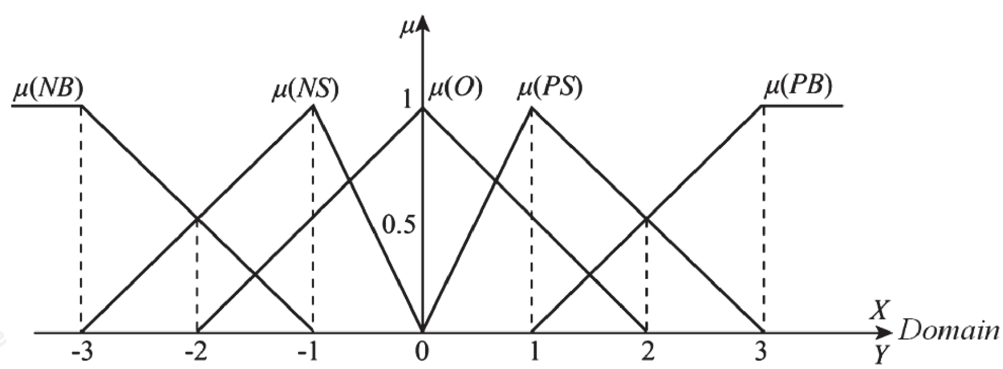

Figure 3.
Membership functions of language variables.

Membership	Language variable						
Quantization level	**−3**	**−2**	**−1**	**0**	**1**	**2**	**3**
PB	0	0	0	0	0	0.5	1
PS	0	0	0	0	1	0.5	0
O	0	0	0.5	1	0.5	0	0
NS	0	0.5	1	0	0	0	0
NB	1	0.5	0	0	0	0	0

Table 1.
Assignment table of fuzzy variables (e, u).

Among them, the subscripts *e* and *u* of language variables *NBe*, *PBu*, etc. indicate that they are language variables of error and control amount, respectively. **Figure 4** shows the fuzzy rule base.

1.3 Adaptive fuzzy control

1.3.1 Components of the fuzzy control system

1.3.1.1 The concept of adaptive control

In the 1950s and 1960s, since classic control was difficult to meet the high control performance requirements of aircraft, rockets, and satellites, a high-performance controller capable of automatically adapting to the changing characteristics of the controlled object, an adaptive controller, was needed.

In order to make the controlled object operate according to the predetermined rules, negative feedback control is used. A natural idea is that when the control performance of the controller does not meet the requirements, the negative feedback control idea is also used to control the controller itself to improve the control performance. This is the basic idea of adaptive control. Therefore, the adaptive controller must have two functions at the same time:

1. According to the operating state of the controlled process, a suitable control amount is given, that is, a control function.

2. According to the control effect of the given control amount, the control decision of the controller is further improved to obtain a better control effect, that is, a learning function.

The adaptive controller performs system identification and control tasks simultaneously. The essence of the adaptive fuzzy controller is to make a control strategy described in language by observing and evaluating the performance of the

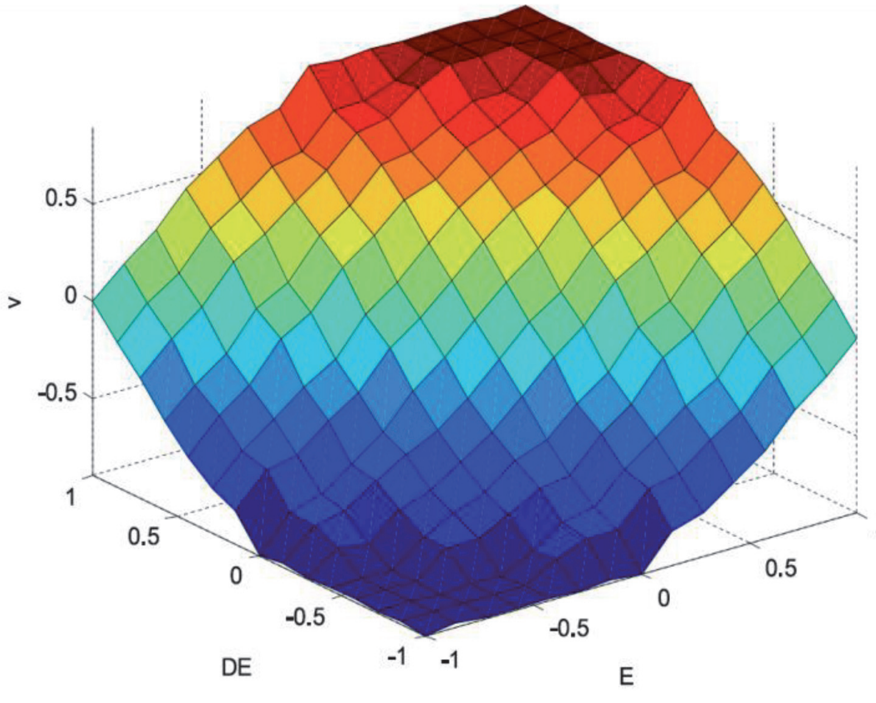

Figure 4.
Control surface of the fuzzy rule base.

controller. There are two types of adaptive control: direct adaptive control and indirect adaptive control. The principle of direct adaptive control is shown in **Figure 5**. It adds an adaptive mechanism to the basic feedback control system. It obtains signals from the original control system. The control performance changes that it can adaptively modify the controller parameters to make the control. Performance remains the same. The principle of indirect adaptive control is shown in **Figure 6**. It uses online identification to identify the parameters of the object, and then uses the identified parameters to adjust the control parameters through the parameter corrector to continuously improve and improve the control performance.

Direct reference adaptive control includes model reference adaptive control (MRAC), while indirect adaptive control is also called self-correcting control (STC).

Introduce fuzzy logic inference system in traditional adaptive control, or act as an adaptive mechanism, or as an object model, or as a controller, or both, forming different forms of adaptive fuzzy control, or fuzzy adaptive control [5].

1.3.1.2. The structure of adaptive fuzzy controller

The adaptive fuzzy controller is based on the basic fuzzy controller, and an adaptive mechanism is added. Its structure is shown in **Figure 7**. The adaptive mechanism in the dashed box in the figure includes three functional blocks, which are:

1. Performance measurement-used to measure the deviation between the actual output characteristics and the expected characteristics in order to provide information for the correction of the control rules, that is, to determine the correction amount P of the output response.

2. Control amount correction—the correction amount of the output response is converted into the correction amount R of the control amount.

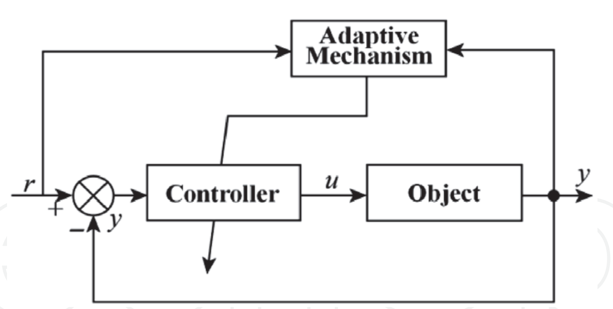

Figure 5.
Block diagram of fuzzy control system structure of direct adaptive control.

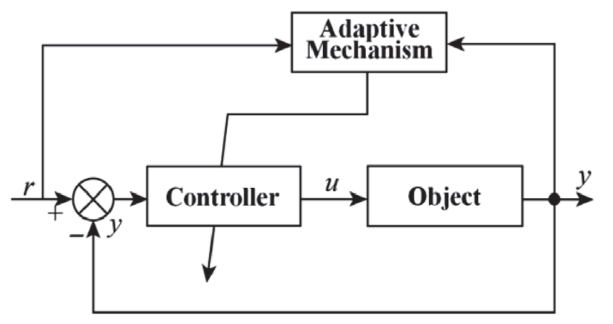

Figure 6.
Structure of indirect adaptive control.

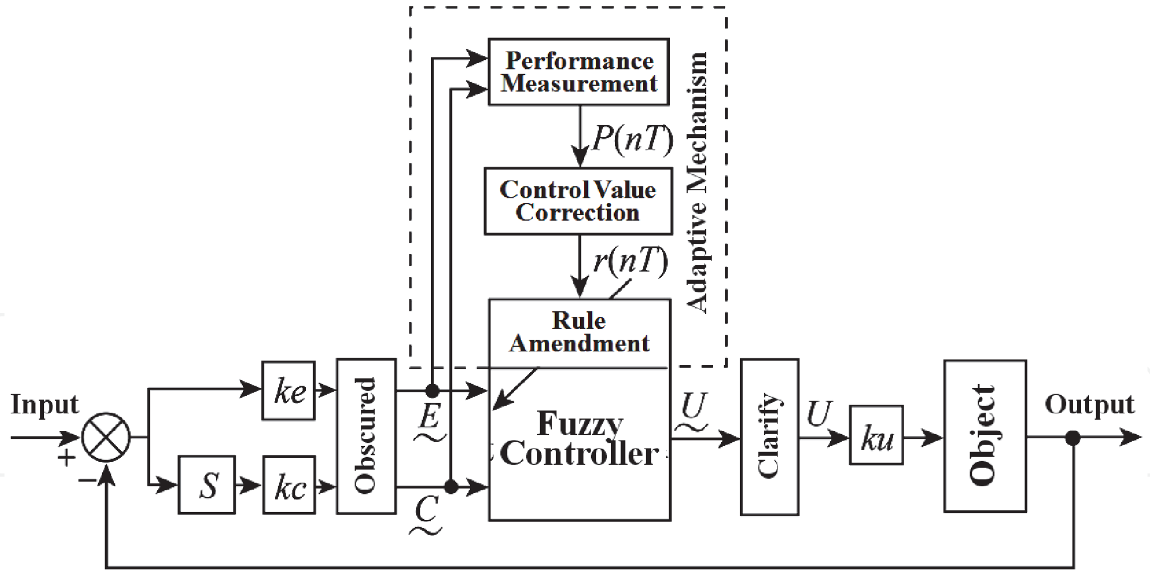

Figure 7.
Structure of the adaptive fuzzy controller.

3. Modification of control rules-correction of control amount is achieved by modifying control rules.

1.3.1.3 Principle of adaptive fuzzy controller

The adaptive fuzzy controller also needs to understand the parameters of the controlled object while controlling the controlled object. Therefore, it is actually a control method that combines fuzzy system identification and fuzzy control. Through identification, we can better "understand" the controlled object so that the controller can "follow" changes in the object and the environment. In this way, the controller itself has a certain ability to adapt to changes, or the adaptive fuzzy controller has higher intelligence.

The three function blocks added by the adaptive fuzzy controller are implemented by software to implement their # functions. The adaptive link can be understood as the introduction of a "soft feedback" inside the fuzzy controller, that is, the feedback of the controller's own performance implemented by software. Through this feedback, the control performance of the controller is continuously adjusted and improved to make the control effect of the control process is sent to the best state.

The above method is still feasible for a system with a single input and single output and which is not critical to the calculation time. The relationship matrix for a multiple input multiple output system is too large for a computer to store and compute.

1.3.2 The principle and method of model reference adaptive fuzzy control

1.3.2.1 Basic principle of model reference adaptive fuzzy control

The model reference adaptive system originates from the concept of self-adaptation of human behavior and causal reasoning (law of cause and effect) being transplanted into the field of control. The causal reasoning model is a general model of the reasoning process that expresses human adaptive characteristics. The causal law model characterizes the qualitative relationship between cause and effect.

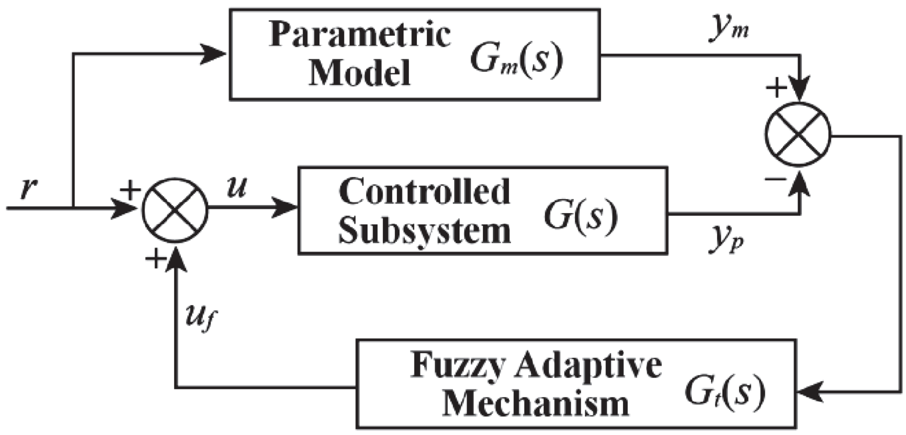

Figure 8.
Structure of model reference adaptive fuzzy controller.

By comparing the model with the real situation, people use adaptive mechanisms instead of people to modify parameters or control strategies to obtain a process that is close to the desired output for control system.

The basic structure of the model reference adaptive fuzzy control system includes three components:

1. Reference model-used to describe the dynamic characteristics of the controlled object or to represent an ideal dynamic model.

2. Controlled subsystem-including the controlled object, feed forward controller and feedback controller, as shown by the dashed box in the Figure.

3. Self-adaptive mechanism—adjust the control parameters of the feed forward controller and feedback controller based on the difference e between the actual output y_P of the controlled object and the reference model output y_m and its changes, so that e = y_m-$y_p \to 0$.

1.3.2.2 Design method of fuzzy adaptive mechanism

The fuzzy adaptive mechanism design method generally has the following two forms:

1. Design fuzzy adaptive mechanism based on fuzzy relation model. The design process based on fuzzy relation model is similar to the design steps of fuzzy control look-up table.

2. Design of fuzzy adaptive mechanism model based on TS fuzzy model, the general structure of the reference fuzzy adaptive system can be expressed in the form of **Figure 8**, where the controlled subsystem is a closed-loop subsystem including the controlled object. The adaptive mechanism generates a fuzzy adaptive signal according to the difference between the output of the reference model and the output of the controlled subsystem, and changes the output of the controlled subsystem to the reference model output [6].

1.3.3 Simulation and programming of adaptive fuzzy control

Adaptive fuzzy control simulation takes the controlled object as Eq. (3).

$$\ddot{x} = -25\dot{x} + 133u \tag{3}$$

Position instruction is sin(πt) take the membership function in Eqs. (4)–(9).

$$\mu_{N3}(x_i) = \frac{1}{(1 + exp\,(5(x + 2)))} \tag{4}$$

$$\mu_{N2}(x_i) = exp\left((x + 1.5)^2\right) \tag{5}$$

$$\mu_{N1}(x_i) = exp\left[((x_i + 0.5))^2\right] \tag{6}$$

$$\mu_{p1}(x_i) = exp\left[-((x_i - 0.5))^2\right] \tag{7}$$

$$\mu_{p2}(x_i) = exp\left[-((x_i - 1.5))^2\right] \tag{8}$$

$$\mu_{p3}(x_i) = \frac{1}{(1 + exp\,(-5(x - 2)))} \tag{9}$$

The initial state matrix of the system is $[1, 0]$, and the initial values of each element in θ are all taken as 0. Control rule show in Eq. (10) and adaptive rule (11) are adopted. Then take $Q = \begin{bmatrix} 50 & 0 \\ 0 & 50 \end{bmatrix}$, $k_1 = 1$, $k_2 = 10$, and adaptive parameter γ = 50.

$$u_D = (x|\theta) = \frac{\sum_{l_1=1}^{m_1} \cdots \sum_{l_n=1}^{m_n} \overline{y_u}^{l_1 \ldots l_n} \left(\prod_{i=1}^{n} \mu_{Ai}^{l_i}(x_i)\right)}{\sum_{l_1=1}^{m_1} \cdots \sum_{l_n=1}^{m_n} \left(\prod_{i=1}^{n} \mu_{Ai}^{l_i}(x_i)\right)} \tag{10}$$

$$\dot{V} = -\frac{1}{2} e^T Q e + \frac{b}{\gamma} (\theta^* - \theta)^T \left[\gamma e^T P_n \zeta(x) - \dot{\theta}\right] - e^T p_n b w \tag{11}$$

According to the membership function, write the MATLAB program as follows:

```
% Adaptive fuzzy approximation
clc % Clear screen
clear all; % Remove workplace variables
close all; % Close the display graphics window
L1 = -3;
L2 = 3;
L = L2-L1; % Fuzzy set change range length
T = 0.001;
x = L1: T: L2; % Range of fuzzy set
figure (1);
for i = 1: 1: 6
    if i = 1
        u = 1 ./ (1 + exp (5 * (x + 2)));
    else if i = 6
        u = 1 ./ (1 + exp (-5 * (x-2)));
    else
    u = exp (-(x + 2.5- (i-1)). ^ 2);
end
    hold on;
    plot (x, u, 'r', 'Line Width', 2);
end
```

```
x label ('x'); y label ('Membership function fuzzy set');
grid on
axis tight
```

The running program is shown in **Figure 9** as a membership function graph.

Directly and adaptively control the internal control objects. The MATLAB program is written as follows. Results show in **Figures 10–12**.

```
% S-function for continuous state equation for controlled object
function [sys, x0, str, ts] = s_function (t, x, u, flag)
switch flag,
% Initialization
    case 0,
        [sys, x0, str, ts] = mdlInitializeSizes; % Initialization function
    case 1,
        sys = mdlDerivatives (t, x, u);% Differential function
% Outputs
    case 3,
        sys = mdlOutputs (t, x, u);% Output function
% Unhandled flags
    case {2, 4, 9}
        sys = [];
% Unexpected flags
    otherwise
        error (['Unhandled flag =', num2str (flag)]);
end
function [sys, x0, str, ts] = mdlInitializeSizes
sizes = simsizes;
sizes.NumContStates = 2;
sizes.NumDiscStates = 0;
sizes.NumOutputs = 2; % 2 outputs
sizes.NumInputs = 1; %1 input
sizes.DirFeedthrough = 0;
sizes.NumSampleTimes = 0;
sys=simsizes(sizes);
x0 = [1 0];
```

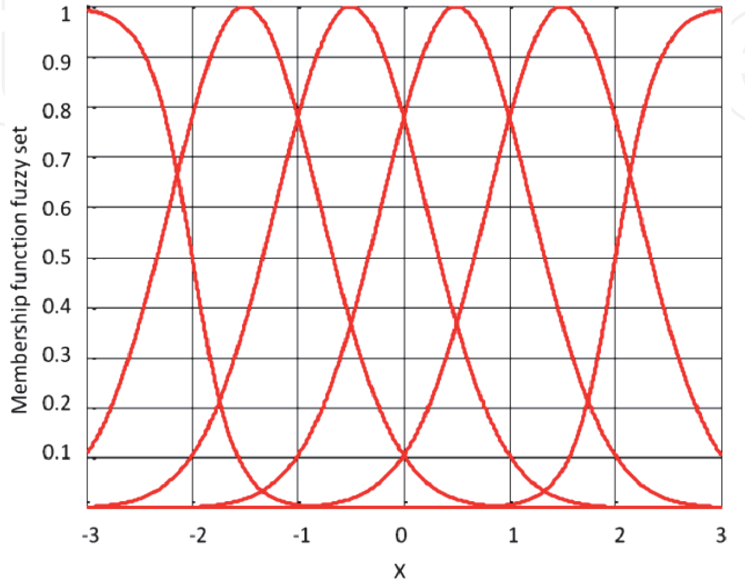

Figure 9.
Membership function graph.

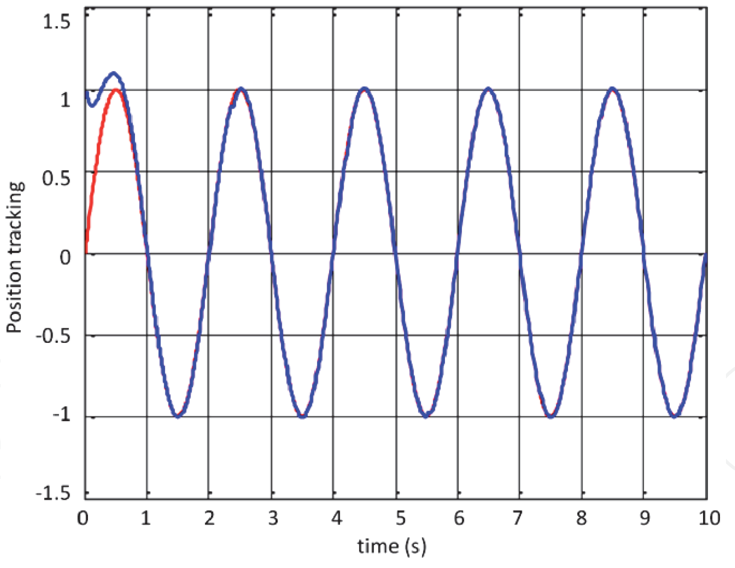

Figure 10.
Simulation result of position tracking.

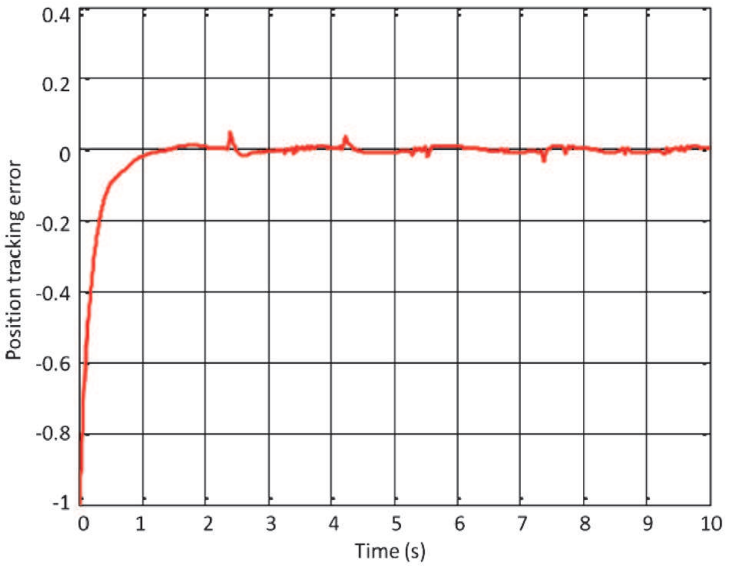

Figure 11.
Simulation result of position tracking error.

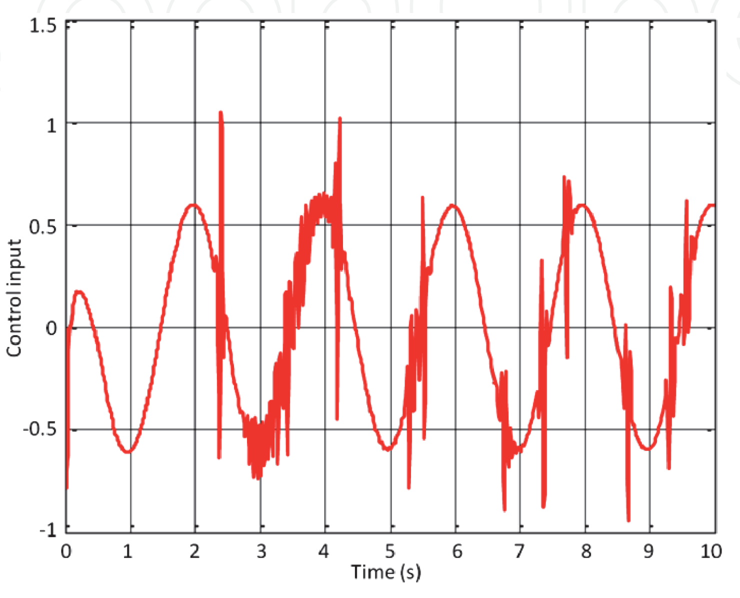

Figure 12.
Simulation result of control input.

```
str = [];
ts=[];
function sys = mdlDerivatives (t, x, u)
% Second-order system
sys (1) = x (2);
sys (2) =-25 * x (2) + 133 * u;
function sys = mdlOutputs (t, x, u)
sys (1) = x (1);
sys (2) = x (2);
% Drawing program writing
close all;
figure (1);
plot (t, y (:, 1), 'r', t, y (:, 2), 'b', 'LineWidth', 2);
xlabel ('time (s)'); ylabel ('Position tracking');
grid on
title ('Location tracking')
figure (2);
plot (t, y (:, 1) -y (:, 2), 'r', 'LineWidth', 2);
xlabel ('time (s)'); ylabel ('Position tracking error');
grid on
title ('Position tracking error')
figure (3);
plot (t, u (:, 1), 'r', 'LineWidth', 2);
xlabel('time(s)');ylabel('Control input');
grid on
title ('Control input signal')
```

2. Neural network

2.1 The connotation of neural network

The neural network model is used to simulate the process of a large number of neurons in the human brain, including information processing, processing, storage, and search. Its main features include (1) the characteristics of distributed storage of information. (2) Information processing and reasoning have the characteristics of parallelism. (3) Information processing has the characteristics of self-organization and self-learning. (4) It has a very strong non-linear mapping capability from input to output [7].

The topology of the neural network connection method is a graph with neurons as nodes and directed connections between nodes as edges. The structure can be divided into two categories: layered and gridded. A neural network with a hierarchical structure consists of several layers. Each layer has a certain number of neurons. Neurons in adjacent layers are unidirectional connected. Normally, neurons in the same layer cannot connect. In a neural network with a network structure, any two neurons may be connected in both directions. The following are several common neural network structures including (1) forward neural networks. (2) Feedback neural network. (3) Integrate neural networks with each other. (4) Hybrid neural network.

Neurons in the human brain pass through the fine structures of many dendrites, collect information from other neurons, and burst electrical activity pulses through the axis. How to adjust the connection weight is reconstructed into different learning algorithms. In order to apply neural networks to solve practical engineering problems, they must be trained. This is neural network teacher learning or supervised learning. And neural network learning usually refers to unsupervised learning of neural networks. In addition, after training the neural network through the sample data set, when new data other than the sample data set appears in the input, the neural network can still obtain new outputs through learning, and can strictly maintain the input–output mapping relationship after the input. The training ability of neural networks is called the generalization ability of neural networks. By changing the structure and parameters of the neural network, you can change the size of the network to make it more suitable for solving specific problems. This process is called the growth and pruning of neural networks [8].

2.2 Types and controls of intelligent control based on neural networks

In the control system, the non-linear mapping capability of neural networks can be used to model complex non-linear objects that are difficult to accurately describe, or to act as controllers, or to optimize calculations, or to perform inference, or fault diagnosis, or both Adaptation of certain functions, etc.

Neural network-based intelligent control this book refers to the collective control of neural network alone control or integration of neural network and other intelligent control methods. The main types of control are the following forms.

1. Neural network direct feedback control. This is a way to directly implement intelligent control using only neural networks. In this control method, the neural network is directly used as a controller, and algorithms such as feedback are used to implement self-learning control.

2. Neural network expert system control. Expert systems are good at expressing knowledge and logical reasoning. Neural networks are better than non-linear mapping and intuitive reasoning. Combining the two to give play to their respective advantages will result in better control results.

3. Neural network fuzzy logic control. Fuzzy systems are good at directly expressing logic and are suitable for directly expressing knowledge. Neural networks are better at learning to express knowledge implicitly through data. The former is suitable for top-down expression, and the latter is suitable for bottom-up learning process. The two are complementary and related. Therefore, their integration can complement each other and better improve the intelligence of the control system. There are three ways to combine neural network and fuzzy logic. First, fuzzy control using fuzzy neural network to drive fuzzy reasoning. This method uses a neural network to directly design multiple membership functions, and combines the neural network as a membership function generator in a fuzzy control system. Second, use neural network to memorize the control of fuzzy rules. An abstract concept value is expressed by a group of neurons with different degrees of excitement, thereby converting abstract empirical rules into input and output samples of a multilayer neural network, and memorizing these samples through a neural network such as a BP network. The use of these experiences for control, in a sense, mimics the way people think about associative memory. Third, the parameters of the fuzzy controller are optimized using a neural network. In addition to the above-mentioned membership functions and fuzzy rules, the factors that affect the control performance in fuzzy control systems also have control parameters such as the quantization factor of error and error change and the output scale factor. These can be optimized using the optimization calculation function of neural network Parameters to improve the performance of the fuzzy control system.

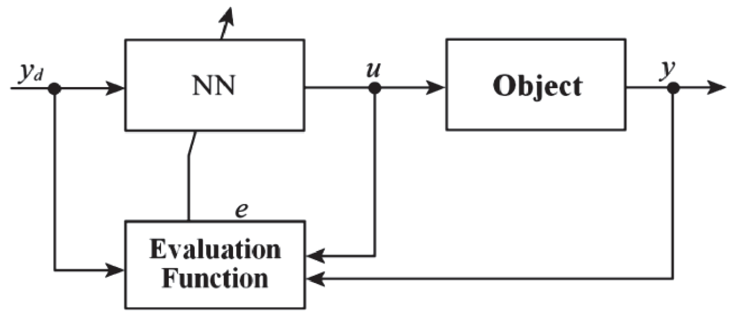

Figure 13.
Structure of model reference adaptive fuzzy controller.

4. Neural network sliding mode control. Variable structure control can be regarded as a special case of fuzzy control, so it belongs to the category of intelligent control. Combining neural network and sliding mode control constitutes neural network sliding mode control. This method classifies the control or state of the system, switches and selects according to changes in the system and the environment, uses the learning ability of the neural network, and improves the sliding mode switching curve through self-learning in an uncertain environment, thereby improving sliding mode the effect of control.

2.3 Neural control based on traditional control theory

The neural network is used as a link or links in a traditional control system to serve as an identifier, controller, estimator, or optimization calculation. There are many ways to do this. Some common ways are summarized as follows.

1. Nerve inverse dynamic control. Let the state observation value of the system be $x(t)$, and its relationship with the control signal $u\ (t)$ is $x(t) = F(u\ (t), x\ (t-1))$. F may be unknown, assuming F is reversible, which can be obtained from $x(t)$, $x(t-1)$, and the dynamic response through training the neural network is $u(t) = H(x(t), x(t-1))$, H is the inverse dynamic of F.

2. Neural PID control. Combining neuron or neural network with conventional PID control, using the learning algorithm of neuron or neural network to optimize and adjust HD control parameters in real-time during the control process according to the dynamic characteristics of the controlled object to achieve online optimization of PID the purpose of controlling performance. Such a composite control form is collectively referred to as neuron PID control or neural HD control.

3. Model reference neural adaptive control. In traditional model reference adaptive control systems, neural networks are used as object models, or as controllers, or as adaptive mechanisms, or to optimize control parameters, or both. Such systems are collectively referred to as model reference neural adaptive control.

4. Nerve self-correcting control. One form of this control structure is the indirect learning control structure of the dual neural network introduced earlier. The control structure of a single neural network is shown in **Figure 13**. The evaluation function is generally taken as $e = yd\text{-}y$, or the following form Eq. (12): [9].

$$e(t) = M_y\left[y_d(t) - y(t)\right] + M_u u(t) \tag{12}$$

Among them, M_y and M_u are matrices of appropriate dimensions. The effectiveness of this method has been confirmed in the underwater robot attitude control. In addition, the combination of neural network and traditional control, as well as endometrial control, neural predictive control, and neural optimal decision control, will not be described in detail.

2.4 Programming of neural network PID controller

Here is a programming example of neural network PID controller simulation, the simulation results are shown in **Figures 14–18**, write the MATLAB program as follows:

```
% Calculation error
    error = [r1 (k) -y1 (k); r2 (k) -y2 (k); r3 (k) -y3 (k)];
    error1 (k) = error (1); error2 (k) = error (2); error3 (k) = error (3);
    J (k) = 0.5 * (error (1) ^ 2 + error (2) ^ 2 + error (3) ^ 2);% adjust size
    ypc = [y1 (k) -y_1 (1); y2 (k) -y_1 (2); y3 (k) -y_1 (3)];
    uhc = [u_1 (1) -u_2 (1); u_1 (2) -u_2 (2); u_1 (3) -u_2 (3)];
```

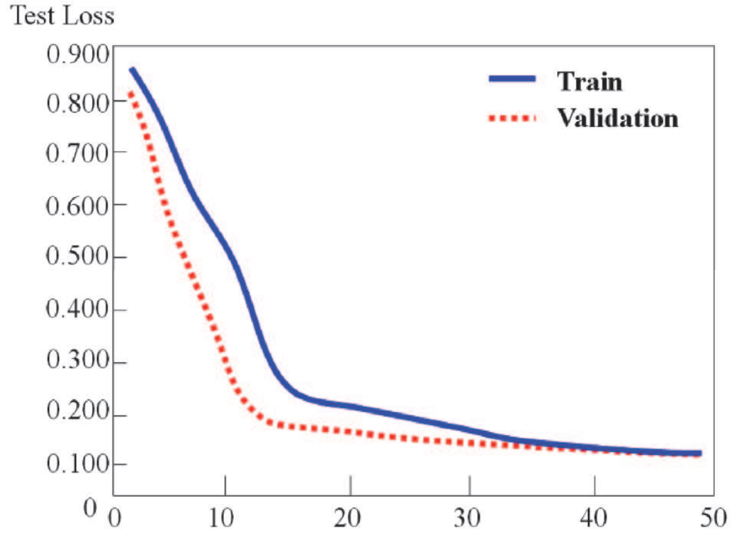

Figure 14.
Simulation result of test loss comparison of train and validation.

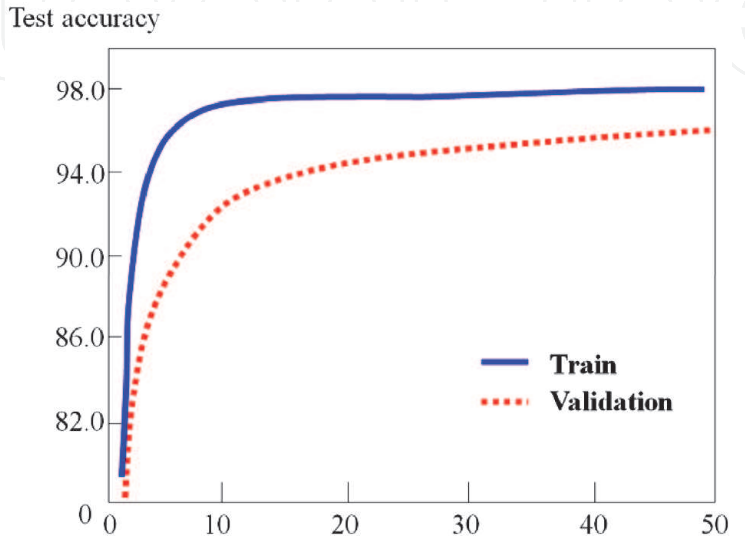

Figure 15.
Simulation result of test accuracy comparison of train and validation.

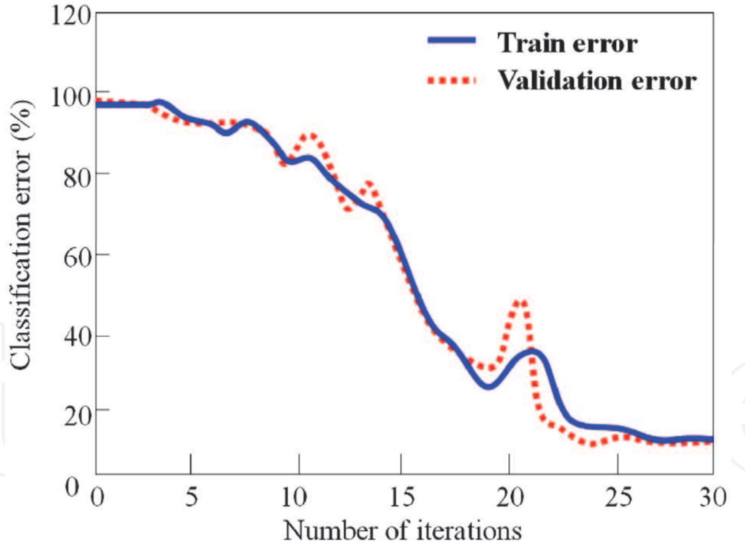

Figure 16.
Simulation result of test error comparison of train and validation.

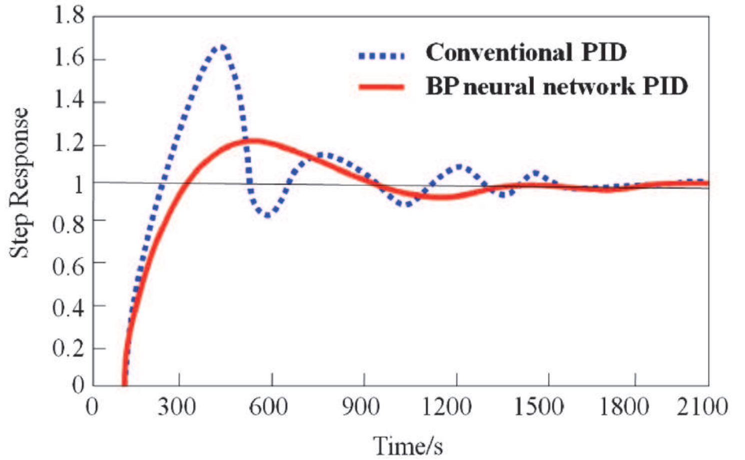

Figure 17.
Step response simulation of conventional PID control and BP neural network PID control.

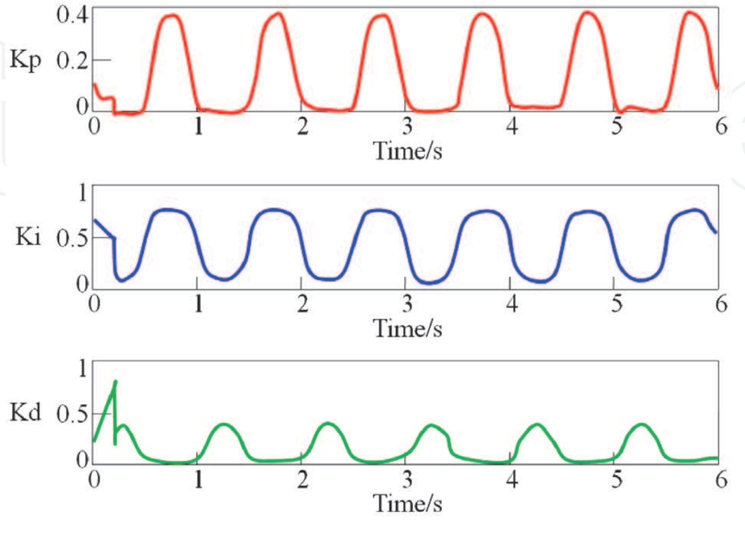

Figure 18.
Change curve of Kp, Ki, Kd parameters.

```
% Hidden layer and output layer weight adjustment
% Adjust w21
Sig1 = sign (ypc ./ (uhc (1) +0.00001));
```

```
    dw21 = sum (error. * Sig1) * qo ';
    w21 = w21 + rate2 * dw21;
    % Adjust w22
    Sig2 = sign (ypc ./ (uh (2) +0.00001));
    dw22 = sum (error. * Sig2) * qo ';
    w22 = w22 + rate2 * dw22;
    % Adjust w23
    Sig3 = sign (ypc ./ (uh (3) +0.00001));
    dw23 = sum (error. * Sig3) * qo ';
    w23 = w23 + rate2 * dw23;
    % Input layer and hidden layer weight adjustment
    delta2 = zeros (3,3);
    wshi = [w21; w22; w23];
    for t = 1: 1: 3
      delta2 (1: 3, t) = error (1: 3). * sign (ypc (1: 3) ./ (uhc (t) +0.00000001));
    end
    for j = 1: 1: 3
      sgn (j) = sign ((h1i (j) -h1i_1 (j)) / (x1i (j) -x1i_1 (j) +0.00001));
    end
s1 = sgn '* [r1 (k), y1 (k)];
    wshi2_1 = wshi (1: 3,1: 3);
    alter = zeros (3,1);
    dws1 = zeros (3,2);
    for j = 1: 1: 3
       for p = 1: 1: 3
          alter (j) = alter (j) + delta2 (p,:) * wshi2_1 (:, j);
       end
    end
    for p = 1: 1: 3
       dws1 (p,:) = alter (p) * s1 (p, :);
    end
    w11 = w11 + rate1 * dws1;
    % Adjust w12
    for j = 1: 1: 3
       sgn (j) = sign ((h2i (j) -h2i_1 (j)) / (x2i (j) -x2i_1 (j) +0.0000001))
    end
    s2 = sgn '* [r2 (k), y2 (k)];
    wshi2_2 = wshi (:, 4: 6);
    alter2 = zeros (3,1);
    dws2 = zeros (3,2);
    for j = 1: 1: 3
    for p = 1: 1: 3
    alter2 (j) = alter2 (j) + delta2 (p,:) * wshi2_2 (:, j);
    end
    end
    for p = 1: 1: 3
    dws2 (p,:) = alter2 (p) * s2 (p, :);
    end
    w12 = w12 + rate1 * dws2;
    % Adjust w13
    for j = 1: 1: 3
    sgn (j) = sign ((h3i (j) -h3i_1 (j)) / (x3i (j) -x3i_1 (j) +0.0000001));
    end
```

```
s3 = sgn '* [r3 (k), y3 (k)];
wshi2_3 = wshi (:, 7: 9);
alter3 = zeros (3,1);
dws3 = zeros (3,2);
for j = 1: 1: 3
for p = 1: 1: 3
alter3 (j) = (alter3 (j) + delta2 (p,:) * wshi2_3 (:, j));
end
end
for p = 1: 1: 3
dws3 (p,:) = alter2 (p) * s3 (p, :);
end
w13 = w13 + rate1 * dws3;
% Parameter update
u_3 = u_2; u_2 = u_1; u_1 = uh;
y_2 = y_1; y_1 = yn;
h1i_1 = h1i; h2i_1 = h2i; h3i_1 = h3i;
x1i_1 = x1i; x2i_1 = x2i; x3i_1 = x3i;
end
time = 0.001 * (1: k);
figure (1)
subplot (3,1,1)
plot (time, r1, 'r-', time, y1, 'b-');
title ('PID neural network control');
ylabel ('Controlled amount 1');
legend ('control the target', 'actual output', 'fontsize', 12);
subplot (3,1,2)
plot (time, r2, 'r-', time, y2, 'b-');
ylabel ('Controlled amount 2');
legend ('control the target', 'actual output', 'fontsize', 12);
axis ([0,0.2,0,1])
subplot (3,1,3)
plot (time, r3, 'r-', time, y3, 'b-');
xlabel ('time / s');
ylabel ('Controlled amount 3');
legend ('control the target', 'actual output', 'fontsize', 12);
print -dtiff -r600
figure (3)
plot (time, u1, 'r-', time, u2, 'g-', time, u3, 'b');
title ('PID control input provided by the neural network to the object');
xlabel ('time'), ylabel ('control law');
legend ('u1', 'u2', 'u3'); grid
figure (4)
plot (time, J, 'r-');
axis ([0,0.1,0,0.5]); grid
title ('network learning objective function J dynamic curve');
xlabel ('time'); ylabel ('control error');
% BPy1 = y1;
% BPy2 = y2;
% BPy3 = y3;
% BPu1 = u1;
% BPu2 = u2;
% BPu3 = u3;
```

```
% BPJ = J
% save BP r1 r2 r3 BPy1 BPy2 BPy3 BPu1 BPu2 BPu3 BPJ
```

3. Expert control and humanoid intelligent control

3.1 Expert control

An expert is someone who has deep theoretical knowledge or rich practical experience in a certain field. Experts' decision-making actions to solve difficult problems can achieve important results because they have accumulated valuable theoretical knowledge and practical experience in their heads. We may use some kind of knowledge acquisition method to store expert knowledge and experience in the professional field into the computer, and rely on its reasoning program to make the computer work close to the level of the expert. It can be based on the special domain knowledge and knowledge provided by one or more human experts. Use experience to reason and judge. An expert system is a computer program system with a large amount of expertise and experience [10].

The basic structure of an expert system usually consists of five parts: a knowledge base, a database, an inference engine, and an interpretation part and knowledge acquisition.

In terms of the main features and structure of the expert system, the industrial production process places several special requirements on the expert control system that are different from general expert systems, including (1) high reliability and long-term continuous operation. (2) Real-time nature of online control. (3) Excellent control performance and anti-interference. (4) Flexible and easy to maintain [11].

Because industrial process control has the aforementioned special requirements for expert control systems, expert control systems control process objects, and domain expert knowledge is usually represented by production rules. Generally speaking, the expert control system consists of the following parts: (1) Database. (2) Rule base. (3) Inference engine. (4) Human-machine interface. (5) Planning.

Constructing an expert control system requires not only complex design and long commissioning cycles, but also a large amount of human, material and financial resources. Therefore, for some controlled objects, considering the control performance indicators, reliability, real-time performance, and performance/price ratio requirements, the expert control system can be simplified.

Expert controller is usually composed of four parts: knowledge base, control rule set, reasoning mechanism and information acquisition and processing. The scale of the knowledge base and control rule base of the expert controller is small, and the reasoning mechanism is simple. Therefore, it can be controlled by microcontroller, programmable controller (PLC), etc. to realize.

According to the characteristics of industrial process control, production rules are used to describe the causality of the controlled process, and control rule sets can be established through fuzzy control rules with adjustment factor analysis and description [12].

Set the input set E and output set U of the expert controller to be Eq. (13) and (14)

$$\begin{aligned} E &= \{-e_n, -e_{n-1}, \cdots, -e_1, 0, e_1, e_2, \cdots, e_n\} \\ U &= \{-u_n, -u_{n-1}, \cdots, -u_1, 0, u_1, u_2, \cdots, u_n\} \end{aligned} \tag{13}$$

$$f(E) = U \tag{14}$$

The control rule set is summarized and summarized based on the knowledge set. It reflects the expertise and experience of experts, and reflects the intelligent control decision-making behavior of people in the operation process. The design control rule set includes the following 6 rules:

1. IF $E > E_{PB}$ THEN U=U_{NB}.

2. IF $E < E_{NB}$ THEN U=U_{PB}.

3. IF $C > C_{PB}$ THEN U=U_{NB}.

4. IF $C < C_{NB}$ THEN U=U_{PB}.

5. IF E•$C < 0$ OR $E = 0$ THEN U=INT[αE+(1-α)C].

6. IF E·C > 0 OR $C = 0$ AND $E \neq 0$ THEN U = INT[βE+(1-β)C+$\gamma \sum_{i=1}^{k} E_i$].

Among them, *E, C*, and *U* are fuzzy variables of error, error change, and control amount, respectively, and the quantization level of *C* is selected exactly the same as *E, U*; and the maximum positive values of *E, C*, and *U,* respectively, and E_{NB}, C_{NB} and U_{NB} are negative maximums of *E, C,* and *U*, respectively; α, β, and γ factors to be adjusted are determined by empirical rules of knowledge concentration; $\sum_{i=1}^{k} E_i$ intelligent integration terms for errors are used to improve the stability of the control system State performance; the symbol INT〔a〕means to take an integer closest to *a*.

Considering that the control decision of the expert controller completely depends on the characteristics of the input data, the controller adopts a data-driven forward reasoning method to sequentially determine the conditions of each rule. If the conditions are met, the rule is executed, otherwise the search is continued. Since there are corresponding controls rules for each of the control input variables £: and C, the target can be searched.

Simulation and practical application show that the above-mentioned expert controller not only has the characteristics of fast dynamic response, small overshoot, and high steady-state accuracy, but also has simple control algorithm programming, flexible control rule modification, good real-time performance, and changes in the parameters of the controlled object. Has strong robustness.

3.2 Human-like intelligent control

Conventional PID control controls the controlled object based on the linear combination of the proportional, integral, and derivative of the controlled system error. According to the mathematical models of different control objects, the three control parameters Kp, Ki, and Kd of the PID are appropriately set to obtain a satisfactory control effect. Linear PID control cannot solve the problem that increasing the control amount can reduce the steady-state error and improve the accuracy, but it will reduce the stability. Physically speaking, the control process is the process of information processing and energy transfer. Therefore, the information processing ability is improved, a more reasonable control law is designed, and the energy transmission of the controlled system is achieved too quickly, stably, and accurately in the shortest time and/or the lowest cost. This is the key problem to be solved in the control system design [13].

It is not enough to use only linear control methods in PID control. It is necessary to introduce some non-linear control methods as needed. The system's dynamic process and transient process, according to the needs of the system's dynamic characteristics, behavior and control performance, use variable gain (gain adaptive), intelligent integration (non-linear integration) and intelligent sampling. This requires expert control experience, heuristics Intuitive judgment and intuitive reasoning rules. Such control decisions are conducive to solving the contradiction between fastness, stability and accuracy in the control system, and can enhance the adaptability and robustness of the system to uncertain factors.

Intelligent control basically imitates human intelligent behavior for control and decision-making. Some scholars have found through experiments that after obtaining the necessary operational training, the artificially implemented control method is close to optimal. This method does not require knowledge of the structural parameters of the object, nor does it require the guidance of an optimal control expert. In the following analysis of the step response characteristics of the second-order system, we can see the basic idea of implementing human-like intelligent control (see **Figure 19**) [14].

It can be found in **Figure 14** (1) that variable gain control should be used in the OA segment. Use a larger gain in the initial section and increase it to a certain stage to reduce the gain so that the system continues to run through the inertia rise. (2) In section AB, the control function shall try its best to reduce the overshoot. In addition to proportional control, the integral control function should be added to enhance the control function through the integral error and make the system output return to the steady state value as soon as possible. (3) In the BC segment, the error starts to decrease, and the system shows a steady state change trend under control. At this time, no integral control operation should be added. (4) The system output decreases in the CD segment, the error changes in the opposite direction, and reaches the maximum value (positive) at point D. At this time, proportional plus integral control should be used. (5) In the DE segment, the system error gradually decreases, and the control effect should not be too strong, otherwise overshoot will occur again.

The basic idea of human-like intelligent control is to use computer to simulate the artificial control behavior in the control process, to maximize the identification and use of the characteristic information provided by the dynamic process of the control system, to make heuristic judgment and intuitive reasoning. This can effectively control objects that lack accurate models.

3.2.1 Characteristic variables of system dynamic behavior

In order to use a computer to automatically realize human-like intelligent control, the system must be able to automatically recognize the dynamic behavior of the control system through some characteristic variables in order to mimic human intelligent control decision-making behavior. In fuzzy control, the error *e* and the

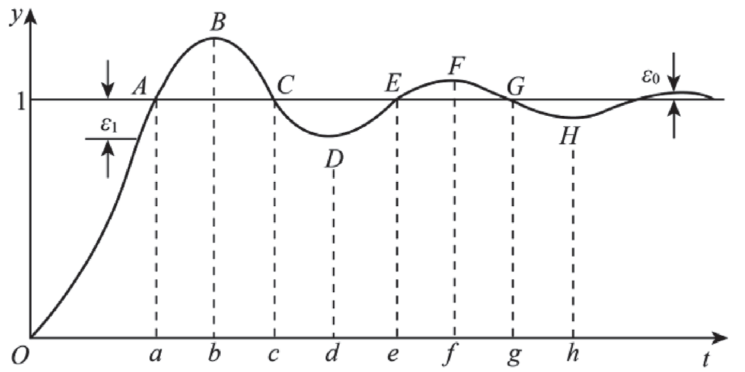

Figure 19.
Unit step response curve for second-order system.

error change Δe are usually selected as the input variables of the fuzzy controller. Generally, the output u of the fuzzy controller can be expressed as Eq. (15).

$$u = f(e, \Delta e) \tag{15}$$

If the control is based on the magnitude of the error e, it is difficult to obtain satisfactory control results for some complex systems. For example, when the controlled system has a large error and it is changing rapidly in the direction of reducing the error, if only based on the large error and not taking into account the rapid change of the error, it is necessary to increase the control amount so that the system eliminates large errors as soon as possible. Error, such control will inevitably lead to the negative consequences of over-regulation and reverse error. When two input variables e and Δe are used for control, the above-mentioned blindness can be avoided. Therefore, for a complex system under manual control, the more people learn about the state, dynamic characteristics, and behavior of the controlled system during the control process, the better the control effect will be.

How to identify the state, dynamic characteristics and behavior of the controlled system according to the input and output information is the first problem to be solved by human-like intelligent control. To this end, starting from the two basic variables of error e and error change Δe, a characteristic variable is designed to identify the characteristic mode of the dynamic process.

3.2.1.1 Characteristic variable $\mathrm{e_n}$•$\Delta \mathrm{e_n}$

The product of the error e and the error change Δe constitutes a characteristic variable describing the dynamic process of the system, and whether the value of the characteristic variable is greater than zero can describe the trend of the system dynamic process error change. Let e_n and e_{n-1} denote the error values of the current and previous sampling moments respectively, then $\Delta e_n = e_n - e_n - 1$. For different stages of the dynamic system response curve shown in **Figure 20**, the values of the characteristic variables e_n•Δe_n are shown in **Table 2**.

When e_n•$\Delta e_n > 0$, as shown in the *AB* and *CD* sections in **Figure 20**, it shows that the dynamic process of the system changes in the direction of increasing error, that is, the absolute value of the error gradually increases. When e_n•$\Delta e_n < 0$, as shown in **Figure 20**, *BC* and *DE*, it shows that the dynamic process of the system changes in the direction of decreasing error, that is, the absolute value of the error gradually decreases. In the control process, the computer can easily recognize the symbol of e_n•Δe_n, so as to grasp the behavior characteristics of the dynamic process of the system, so as to better formulate the next control strategy.

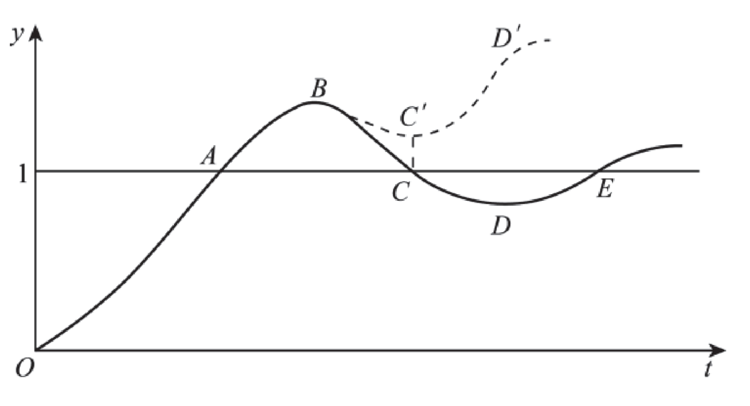

Figure 20.
Curve of dynamic process.

	OA part	AB part	BC part	CD part	DE part
e_n	>0	<0	<0	>0	>0
Δe_n	<0	<0	>0	>0	<0
$e_n \bullet \Delta e_n$	<0	>0	<0	>0	<0

Table 2.
Sign change of characteristic variables.

3.2.1.2 Characteristic variable $e \bullet \Delta e$

The absolute value of the ratio of the error change Δe to the error e is defined as the characteristic variable describing the error change trend in the dynamic process of the system. The combined use of $|\Delta e/e|$ and $e_n \bullet \Delta e_n$ can further divide the characteristics of the dynamic process and facilitate the capture of different modes of the dynamic process. For example, in **Figure 19**, the *AB* segment of the curve can be subdivided into the following three cases:

1. The segment is close to the point A: $e_n \bullet \Delta e_n > 0$ and $|\Delta e/e| > \alpha$ indicate a mode in which the dynamic process presents a small error and a large error change.

2. The AB segment is near the middle part: $e_n \bullet \Delta e_n > 0$ and $\beta < |\Delta e/e| < \alpha$ indicates that the magnitude of the error and the variation of the dynamic process are in a medium state.

3. Segment AB is close to point B: $e \bullet \Delta e > 0$ and $|\Delta e/e| < \beta$ indicates that the dynamic process presents a mode with large errors and small error changes.

The above-mentioned α and β are constants set according to the needs of control, and there are α > β. Similarly, readers of the BC, CD, and DE segments of the curve in **Figure 15** can perform similar analysis.

3.2.1.3 Characteristic variable $\Delta e_n \bullet \Delta e_n - 1$

The product of two adjacent error changes is defined as the characteristic variable that characterizes the extreme state of the error. If $\Delta e_n \bullet \Delta e_n - 1 < 0$, it means that the extreme value appears; if $\Delta e_n \bullet \Delta e_n - 1 > 0$, it means that there is no extreme value. The combination of the characteristic variables $\Delta e_n \bullet \Delta e_n - 1$ and $e_n \bullet \Delta e_n - 1$ can determine the change trend of the dynamic process when the error has an extreme value. As shown in **Figure 19**, extreme values appear at points B and C ‘, But their $e_n \bullet \Delta e_n$ values have opposite signs like below:

Point B: $\Delta e_n \bullet \Delta e_n - 1 < 0$, the error of $e_n \bullet \Delta e_n$ tends to decrease after point B.
Point C′: $\Delta e_n \bullet \Delta e_n - 1 < 0$, $e_n \bullet \Delta e_n > 0$, the error gradually increases after point C′.

3.2.1.4 Characteristic variables $|\Delta e_n \bullet \Delta e_n - 1|$

The magnitude of the absolute value of the ratio of the error change at the current moment to the error change at the previous moment is defined as the characteristic variable describing the local change trend of the system error. It also indirectly indicates the effect of early control. If the ratio is large, it indicates that the effect of early control is not significant; if the ratio is small, it indicates that the effect of early control is significant.

3.2.1.5 Characteristic variable $\Delta\ (\Delta \mathrm{e})$

The sign of the change rate (secondary difference) of the error change is defined as a characteristic quantity that describes the dynamic process as overshoot or callback. For example, for the curve shown in **Figure 19**, there are two cases:

1. ABC segment: $\Delta(\Delta e) > 0$, it is in the overshoot segment.

2. CDE segment: $\Delta(\Delta e) < 0$, which is in the callback segment.

The essential characteristics of the above-designed characteristic variables are that they are not an absolute quantity, but a symbol variable, or a relative quantity. Symbol variables are used to characterize the direction of the dynamic process change trend, and relative quantities are used to characterize the speed of the dynamic process change. The above-mentioned symbol variables and characteristic variables (relative quantities) that characterize the degree of change in a dynamic process are collectively referred to as qualitative variables.

In order to use computers to realize human-like intelligent control, it is necessary to try to teach human operation experience, qualitative knowledge and intuitive reasoning to the computer, and let it apply this knowledge through flexible and flexible judgment, reasoning and control algorithms to perform human-like intelligent control. The main source of online information obtained by a computer is the input R and output Y of the system, from which the error e and the error change Δe can be calculated. Through e and Δe, the characteristic quantities that characterize the dynamic characteristics of the system can be further obtained. The computer can capture the characteristic information of the dynamic process with the aid of the above-mentioned characteristic quantities, and recognize the dynamic behavior of the system as a basis for control decisions. According to the dynamic characteristics and dynamic behavior of the system, the most effective control form is selected from a variety of control modes to precisely control the controlled object. Computers can use qualitative knowledge and intuitive reasoning in the control process. This is fundamentally different from traditional control theories, and it is precisely this point that embodies human intelligence. This method solves the contradiction of speed, stability and accuracy in the control process very well.

3.2.2 Humanoid intelligent control principle

The composition of human-like intelligent controller is similar to the basic structure of an expert controller, which consists of the following four parts.

1. Acquisition and processing of characteristic information. According to the input and output sampling data, the current time error and error change are calculated, and then the characteristic variables necessary to identify the controlled dynamic process mode are obtained.

2. Feature pattern set. The feature pattern set stores certain feature pattern classes, which also include necessary parameters, thresholds, empirical data, and control parameters. It is similar to the knowledge base in an expert controller.

3. Pattern recognition. The pattern recognition plays the role of an inference mechanism. According to the obtained feature variables at the current time, it searches for feature pattern classes that match the constraints provided, and provides prerequisites for control decisions.

4. Control rule set. The control rule set is actually a rule-based controller. The process of control decision is to implement a mapping from the feature pattern set to the control rule set. In general, the number of feature patterns is greater than or equal to the number of control rules.

The working process of the human-like intelligent controller can be summarized into three steps: First, the system judges the characteristic mode of the dynamic process according to the calculated characteristic variables; second, the inference mechanism searches for a matching control rule according to the characteristic mode class; third, the controller executes the above control rules to control the controlled object [15].

This completes a step-by-step intelligent control algorithm, and then cyclically controls step by step until the error of the controlled system reaches the desired index.

3.3 Multiple modes of human-like intelligent control

A variety of human-like intelligent control modes have been formed to imitate human control and decision-making processes: humanoid intelligent switch control, humanoid proportional control, humanoid intelligent integral control, humanoid intelligent sampling control, and humanoid extreme value sampling and control. In addition, in the human-like intelligent control, a combination of variable gain proportional control, proportional differential control, and open-loop and closed-loop control is also used.

3.3.1 Human intelligence integration principle

3.3.1.1 Human-like intelligent integration principle

The introduction of integral control in the control system is an important way to reduce the steady-state error of the system. **Figure 21(c)** shows the integral process of the integral control action on the error in conventional PID control. This integral effect simulates human memory characteristics to a certain extent. It "remembers" all the information about the existence and changes of errors. The disadvantages of the integral control function based on this integral form are: first, the integral control function is not targeted, and sometimes does not meet the objective needs of the control system; second, because this integral effect is always integrated as long as the error exists, it is easy to cause integral saturation in the application of actual practice, which will reduce the rapidity of the system. Third, the integral parameters of this integral control are not easy to select, and improper selection will cause the system to oscillate.

The reason why the integral control function is not good is that the integral control function does not well reflect the intelligent control decision-making thoughts of experienced operators. In the integral curve interval (a, 6) in **Figure 21(c)**, the integral effect is opposite to the control effect of an experienced operator. At this time, the system has overshoot. The correct control strategy should be to add a negative control value to the constant value to reduce the overshoot and reduce the error as soon as possible. However, the integral control effect in this interval increases a positive control amount. This is because the integral result in the $(0, \alpha)$ interval is difficult to be offset and the sign is changed, so the integral control amount remains positive. As a result, the system overshoot cannot be reduced quickly, which prolongs the transition process time of the system.

In the $(6, c)$ section of the above integral curve, the system error changes from a maximum value to a decreasing direction, and there is a trend of steady state change. At this time, a certain proportional control effect should be added, but the integral control effect should not be added. Otherwise, it will cause system callback.

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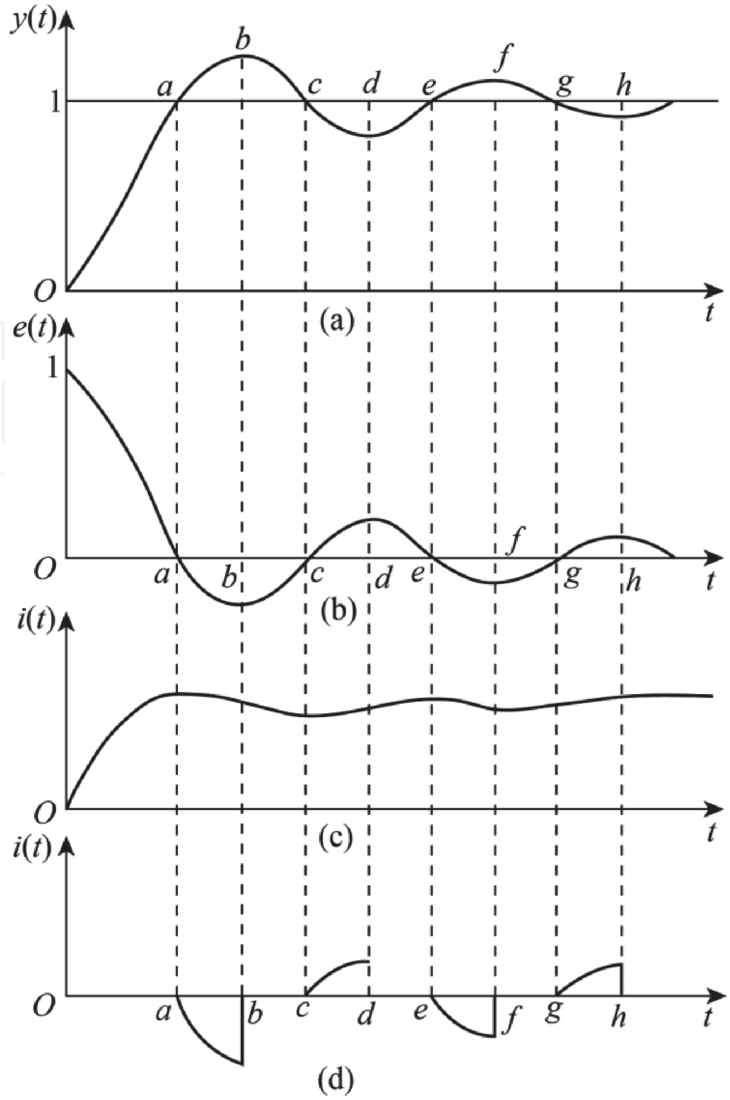

Figure 21.
Error and error integration curve. (a) (y (t)) Unit step response curve for second-order system. (b) (e (t)) Unit step response curve for second-order system. (c) In conventional PID control Integral control is the process of integrating errors. (D) Integrate on equal intervals.

In order to overcome the shortcomings of the integral control function described above, the integral curve shown in **Figure 21(d)** is used, that is, the integration is performed in the intervals (a, b), (c, d), and (e, f). The integral can provide the correct additional control amount for the integral control function in a timely manner, and can effectively suppress the increase of system error; while in the interval (0, a), (b, c), and (d, e), stop integral role to facilitate the system to transition to a steady state by virtue of inertia. At this time, the system is not in a state of out of control, it is also restricted by control functions such as proportion.

This integral function better simulates human memory characteristics and human-like intelligent control strategies. It selectively "remembers" useful information and "forgets" useless information, so it can overcome the shortcomings of general integral control. It has the characteristics of non-linear integration of human-like intelligence, which is called such integration of human-like intelligence.

3.3.1.2 Human-like intelligent integration control algorithm

In order to introduce the function of intelligent integration into the control algorithm, we must first solve the problem of logical judgment of introducing intelligent integration.

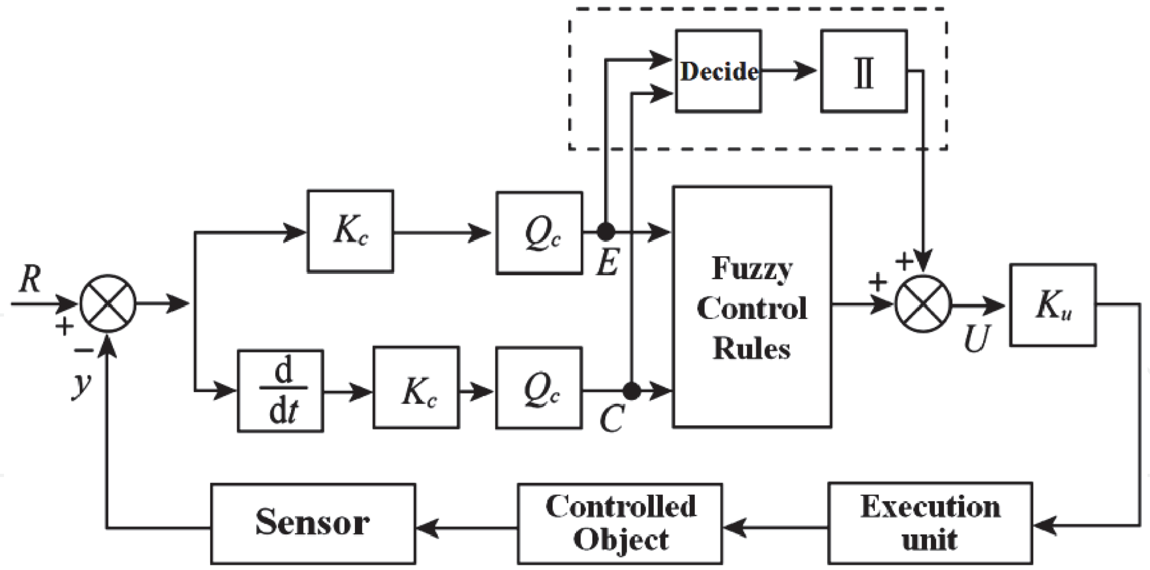

Figure 22.
Structure of a humanoid intelligent controller.

This condition can be determined by comparing the intelligent integration curve in **Figure 21** with **Figure 22** and **Table 2** [16].

When the error e_n and the error change Δe_n at the current sampling time have the same sign, that is, $e_n \bullet \Delta e_n > 0$, the error is integrated; on the contrary, the error e_n and the error change Δe_n have different signs, that is, when $e_n \bullet \Delta e_n < 0$, errors are not integrated. This is the basic condition for introducing intelligent integration. Considering the extreme points of errors and error changes, that is, the boundary conditions, the conditions for introducing intelligent integration and not introducing intelligent integration can be synthesized as follows:

When $e \bullet \Delta e > 0$ or $\Delta e = 0$ *and* $e \neq 0$, the error is integrated, that is, intelligent integration; when $e \bullet \Delta e < 0$ *or* $e = 0$, the error is not integrated, that is, no integration effect is introduced.

The digital simulation results show that the human-integrated intelligent integral control algorithm significantly improves the steady-state accuracy of the fuzzy control system due to the introduction of intelligent integral control. Compared with ordinary fuzzy controllers, the human-integrated intelligent integral control algorithm has the advantage of high steady-state accuracy. Compared with conventional PID control, this control algorithm has the advantages of fast response speed, small overshoot, or no overshoot. Therefore, this is a control algorithm with simple structure and good control performance for intelligent control.

3.3.2 Multiple modes of human-like intelligent control

The computer control systems of most production processes are continuous discrete hybrid systems. In such a system, the detection of time-continuous signals and the output of computer-controlled quantities, considering the problem of signal reproduction, require the correct selection of discrete-time sampling periods. In the control process, the main consideration is to help improve the control quality as much as possible.

3.3.2.1 Effect of sampling period on digital control

The upper limit of the sampling period is selected, but the choice of the lower limit of the sampling period is restricted by many factors. The smaller the sampling period is better to reproduce the signal. However, if the sampling period is too small, the signal-to-noise ratio is low, the quantization noise is large, and it is easy to be interfered, which affects the control performance. In process control, the lower limit of the control cycle selection is limited by the control algorithm operation time. Therefore, the sampling period and the control period are not both as small as possible.

As for the analog design method of the digital controller, the smaller the sampling period, the closer the characteristics of the digital controller are to the characteristics of the analog controller. As for the discrete design methods of digital controllers, most are based on the discretized object model. The discretization model of the object depends on the selection of the sampling period, so the sampling period not only affects the distribution of the zero and pole positions of the model, but also affects the accuracy of the model. Too long a sampling period may even lead to the loss of useful high-frequency information, thereby reducing the model order.

3.3.2.2 Human-like intelligent sampling control for lag process

A large number of controlled processes have varying degrees of time lag, which brings difficulties to the process system. The ratio of the lag time to the capacity lag time constant T reflects the difficulty of control. As the τ/T value increases, the difficulty of control increases accordingly. When approaching or exceeding T, the effect of using ordinary PID control is very poor, and Smith predictive control must be used. However, Smith control requires an accurate controlled process model, and complex controlled processes are often difficult to establish accurate mathematical models. Therefore, many improvements have been made to Smith control, and some control algorithms have emerged to overcome lag. Nevertheless, it should be said that the problem of large lag process control is still a topic of great concern in the control field.

As we all know, for an object with a pure lag time τ, its control effect must be reflected in time τ. Therefore, control within time is of no value, so the sampling control shown in **Figure 23** is generated. The sampling period T_s is slightly larger than τ, and the control time (on time) Δt is about $1/10\ T_s$. This choice will bring two disadvantages: first, the interference and sampling will be seriously out of sync. Because the pure lag time of the controlled process is generally large, T_s is chosen to be large, and the control time Δt is very small. In this way, the system is in an open-loop state during the $T_s - \Delta t$ time of each sampling cycle, and some urgent needs cannot be obtained. Useful information such as changes in output $y(t)$ caused by fixed-value disturbances or a given input that requires $y(t)$ to track as quickly as possible. Second, the feedback information obtained is too small and untargeted, which makes the control in a blind state, resulting in a long transition process.

The disadvantages of the above sampling control are passive waiting and blind control. In short, such control lacks the intelligent sampling characteristics of the lag

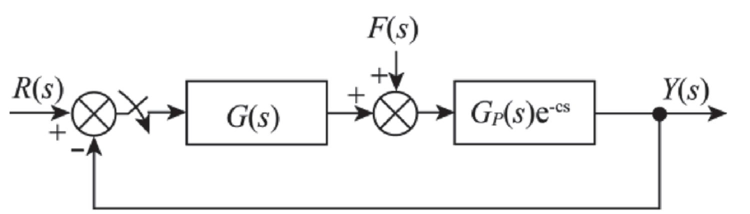

Figure 23.
Sampling control principle.

process of manual control. The basic strategy of manual sampling control to overcome large lags can be described as follows:

$$\text{Wait} \to \text{look} \to \text{tune} \to \text{wait again} \to \text{look again} \to \text{adjust again} \ldots\ldots$$

According to the above control strategy, the principle of a human-like intelligent sampling control system is shown in **Figure 24**. Among them, INT indicates intelligent device; $F(s)$ indicates fixed value interference; $G_{cj}(s)$ indicates controller; $Y(s)$ indicates controlled variable; $G_p(s)e^{-\tau s}$ indicates controlled object; B indicates intermediate feedback coefficient; $R(s)$ indicates interference; P takes the constant "1" or "0".

The function of the intelligent device is to control an intelligent sampling switch K, which "opens" or "closes" when certain conditions are met, that is shown in Eq. (11),

$$K = \begin{cases} 0 \ \text{(Disconnect)} & e \cdot \dot{e} < 0 \text{ or } |e| < \delta \\ 1 \ \text{(Closed)} & e \cdot \dot{e} > 0 \text{ or } \dot{e} = 0, |e| \geq \delta \end{cases} \tag{16}$$

In the formula, e, $\dot{e}$ are the error and the first derivative of the error; δ is the insensitive region.

When the controlled variable deviates from the expected value, the smart device sends a signal that the K switch is closed for sampling, and the controller controls in time until the controlled variable has a tendency to return to a balanced position; when the controlled system error value is within the allowable range, switch K disconnect, the system is in an open-loop working state. At this time, the energy required to be maintained by the object is supplied by the controller or the stored energy of the object.

In **Figure 24**, $G_{cj}(s)$ represents the j^{th} controller $j \in (1,2)$, which is attractive considering that the given interference and fixed value interference often have different control laws and effects. Its selection is made automatically by the logical relationship of the design like Eq. (9):

$$G_{cj}(s) = \begin{cases} G_{c1}(s), & dc(t)/dt \neq 0 \\ G_{c2}(s), & dc(t)/dt = 0 \end{cases} \tag{17}$$

Among them, $c(t) = L^{-1}\left[\frac{1}{T_s+1} R(s)\right]$, T is determined as needed. In this way, the adaptability and effectiveness of the controller are enhanced, and it is ensured that

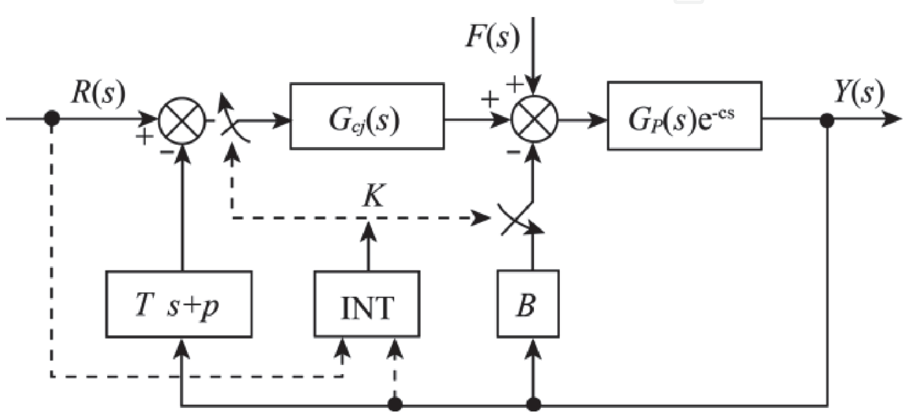

Figure 24.
Intelligent sampling control schematic diagram.

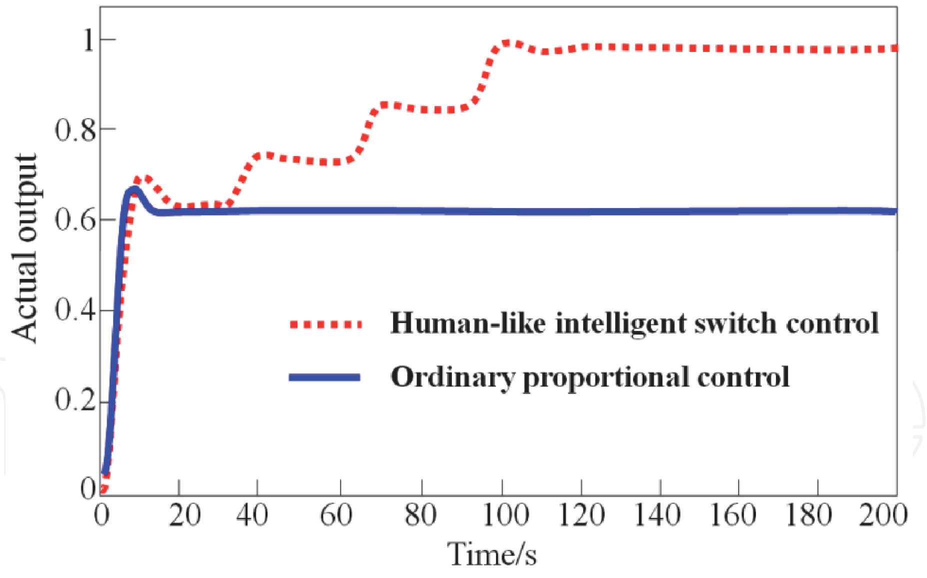

Figure 25.
Human-like intelligent switch control simulation result.

the corresponding controller is selected with different interference. The introduction of intermediate proportional feedback B is mainly for design convenience.

Through further analysis of the above-mentioned intelligent sampling control mechanism, it can be seen that when the switch K is closed and the system is in closed-loop control, whether the system is a follow-up system or a fixed value system, $e^{-\tau s}$ will appear in the characteristic equation, but by setting appropriately due to the logic judgment function of the smart device, the control parameters of the smart device can be established only in a short period of time, so that the unstable factors are eliminated. When the switch is open and the system is in open loop, $e^{-\tau s}$ has no effect on stability. In the above-mentioned intelligent mining control scheme, a smart device is used to determine whether the system is open-loop or closed-loop. In the open-loop process, the controller is in the active waiting phase with an observation function. The purpose of this waiting is to prepare for better control. In the closed-loop process, the controller is in the control phase, which is a manifestation of waiting action for strongly targeted. This control method cleverly avoids the adverse effects brought by $e^{-\tau s}$, and successfully solves the stability problem of the system.

Intelligent sampling control is a novel control method with open loop in the closed loop and closed loop in the open loop. Its entire working process is similar to an experienced operator. It can continuously observe and perform real-time correction as required. Therefore, this control has strong robustness and fastness, and can be easily realized by a microcomputer program.

3.3.3 Programming of human-like intelligent control

Here is a programming example of human-like intelligent switch control simulation, the simulation results are shown in **Figure 25**, write the MATLAB program as follows:

```
k = 1;% scaling factor K
g1 = tf (1, [8 6 1]);% continuous system model G (s)
g2 = feedback (k * g1,1);
tt = 1;
y = [0 0.0329];% output matrix initialization
u = ones (1,100);% input matrix initialization
```

```
u (1) = 0;
e = [0 0.9671];% deviation matrix initialization
for n = 3: 1: 200
    e (n) = k * (u (n-1) -y (n-1));
    if (e (n) -e (n-1) <= 0.0001) & (y (n-1) <= 1)% Judge whether the steady-state and boundary conditions are satisfied
    tt = tt-1;
        if tt == 0% judging whether it is within a switching action period
            u = (u (n) + 0.31 * e (n)) * ones (1,200);% Switch action content
            tt = 40;% set smart switch action period
        end
    end
    e (n) = k * (u (n-1) -y (n-1));
    y (n) = 1.489 * y (n-1) -0.549 * y (n-2) + 0.0329 * e (n-1) + 0.0269 * e (n-2);% difference equation
end
t = 0: 1: n-1;
g3 = step (g2, t);
graphical output of plot (t, y, t, g3)% response curve
```

Here is a programming example of human-like intelligent integral control simulation, the simulation results are shown in **Figure 26**, write the MATLAB program as follows:

```
y = [0 0.132];% output matrix initialization
u = ones (1,1000);% input matrix initialization
u (1) = 0;
e = [0 0.868];% deviation matrix initialization
c = [0 0];% process matrix initialization
kp = 0.803;% PID scale factor
ki = 0.282;% PID integration coefficient
kd = 0.02;% PID differential coefficient
esum = e (2);
for n = 3: 1: 100% conventional PID control system for reference
    y (n) = 1.559 * y (n-1) -0.559 * y (n-2) + 0.3 * c (n-1) + 0.1 * c (n-2);
    e (n) = u (n) -y (n);
```

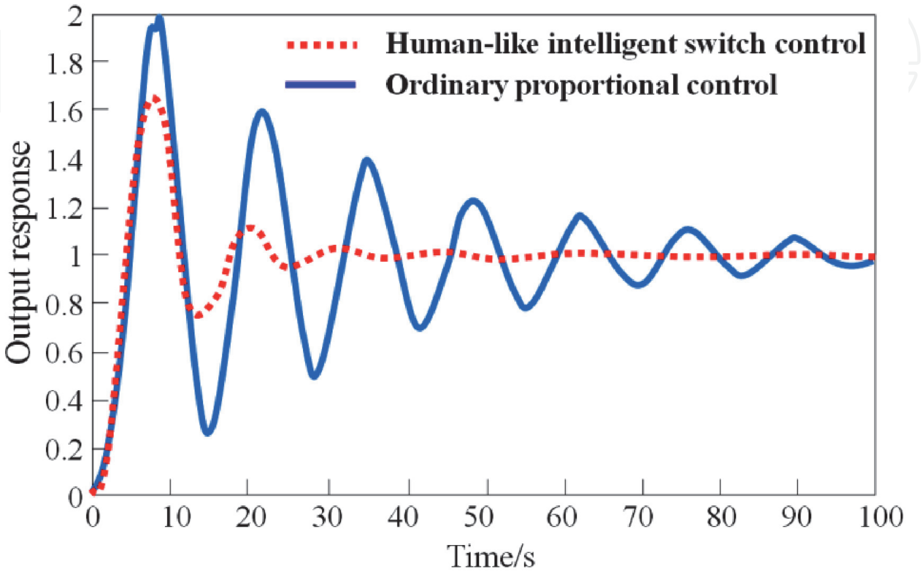

Figure 26.
Intelligent sampling control schematic diagram.

```
        esum = esum + e (n);% deviation summation
        c (n) = kp * (e (n)) + kd * (e (n) -e (n-1)) + ki * esum;% PID link output
        y (n) = 1.559 * y (n-1) -0.559 * y (n-2) + 0.3 * c (n-1) + 0.1 * c (n-2);% c (n)
signal drives the differential equation
    end
    t = 0: 1: n-1;
    plot (t, y)% response curve output
    for n = 3: 1: 100% humanoid intelligent integral control
        y (n) = 1.559 * y (n-1) -0.559 * y (n-2) + 0.3 * c (n-1) + 0.1 * c (n-2);
        e (n) = u (n) -y (n);
        esum = esum + e (n);
        edrta = e (n) * (e (n) -e (n-1));
        if (edrta> 0) & (e (n) ~ = 0)
            c (n) = kp * (e (n)) + kd * (e (n) -e (n-1)) + ki * esum;% for integration
        else
            c (n) = kp * e (n) + kd * (e (n) -e (n-1));
        end
        y (n) = 1.559 * y (n-1) -0.559 * y (n-2) + 0.3 * c (n-1) + 0.1 * c (n-2);
    end
    t = 0: 1: n-1;
    plot (t, y, 'r')% response curve output
```

4. Hierarchical intelligent control and learning control

Large systems usually have the following characteristics: the high-level order of the system, a large number of subsystems and interrelationships, a large number of system evaluation goals, and conflicts between different goals. People studying complex problems usually deal with them at different levels. Similarly, more complex large-scale system control problems are usually broken down into several interrelated subsystem control problems to deal with. Large-scale complex control systems use multi-level and multi-objective control to form a pyramid-like hierarchical control structure. Aiming at the large system control form, according to the information exchange method and related processing methods, it is generally divided into three basic forms: decentralized control, distributed control and hierarchical control. The main structure of the large-scale system control hierarchy includes multiple descriptions, multi-level descriptions, and multi-level descriptions. According to the number of decision-making objectives, the system can be divided into single-stage single-objective systems, single-stage multi-objective systems, and multi-stage multi-objective systems [17].

Regarding the hierarchical control principle of the aforementioned pyramid control structure, the configured controller receives information from an upper-level controller (or a decision unit) and is used to control the controller (or a subsystem) at a lower level. The possible conflicts between controllers depend on the coordination of the superior controller (or coordinator). There are many methods for coordination, but most of them are based on the two basic principles of association prediction coordination and association balance coordination.

4.1 Structure and basic principle of hierarchical intelligent control

The human central nervous system is organized according to a multilayer structure. Therefore, the multi-level hierarchical control structure has become a typical structure of intelligent control. Multilevel hierarchical intelligent control system is a branch of intelligent control. It was first applied in industrial practice and it played an important role in the formation of intelligent control systems. Hierarchical intelligent control structure, according to the intelligence level, it is divided into three levels: organization level, coordination level and control level. Hierarchical intelligent control principle uses the principles and methods of human intelligence, such as human organizers and coordinators, to have the ability to use and process knowledge, and have different degrees of self-learning ability to achieve control purposes. The principle of multi-level and multi-level hierarchical intelligent control of large-scale systems has three characteristics: (1) The more high-level units, the larger the scope of influence on system behavior, and therefore requires higher decision-making intelligence. (2) The decision cycle of the high-level unit is longer than the decision cycle of the lower unit, which mainly deals with factors that involve system behavior and change slowly. (3) The higher the level, the more uncertain the description of the problem, and the more difficult it is to formulate quantitatively. Therefore, the hierarchical intelligent control system is based on the aforementioned principle: accuracy increases as intelligence decreases. Under the unified organization of high-level organizers, multi-layer intelligent control systems can achieve optimal control of complex systems [18].

4.2 Hierarchical learning control system

4.2.1 The concept of learning control

Learning is one of the basic intelligences of people. Learning is to gain knowledge. Therefore, learning control that simulates human learning intelligent behavior in control belongs to the category of intelligent control.

Learning control means that if a system can learn the information inherent in the unknown characteristics of a process or its environment, and use the obtained experience for further estimation, classification, decision-making and control, so that the quality of the system can be obtained. Improve, and then call this system a learning system. The learning information obtained by the learning system is used to control the process with unknown characteristics. Such a system is called a learning control system.

The unknown environment in the learning control system includes the controlled dynamic process and its interference. The learning control law can be different learning control algorithms. The memory is used to store the control information and related data in the control process. The performance index evaluation is to control the learning control. The experience gained in the process is used to continuously estimate the characteristics of unknown processes for better decision-making control.

Because there are many ways to implement the learning control algorithm, the composition of the learning control system will also have different structural forms due to the different learning algorithms.

4.2.2 The main form of learning control

First, adaptive control with learning function. The adaptive control system should have two functions: one is a conventional control function, which is implemented by a closed-loop feedback control loop; the other is a learning function, which is implemented by another feedback control loop composed of an adaptive mechanism, and its control object is the controller itself.

The adaptive control system has a learning function, but the structure of this learning is different from the structure of the learning control system. The learning function of adaptive control is the feedback and evaluation of control performance of conventional controllers, and then the parameters or structure of controllers are adjusted or corrected online through adaptive mechanisms, so that the next step of control performance is better than the previous step. Yes, this is learning. It can be considered that the adaptive learning system is a two-level hierarchical control structure composed of a double closed-loop control system. The conventional control loop is a low-level form of a hierarchical structure, which completes the direct control of the controlled object. The second loop including the adaptive mechanism and the conventional controller is a high-level form of the hierarchical structure. The feedback control form completes the learning function of the controller control behavior.

The iterative learning control system and the repeated learning control system do not have a two-level hierarchical structure like the adaptive control system, but only increase the memory to remember the past control experience. The learning in iterative control is realized through the empirical memory of "weighted sum of control action and error" in the past. The assumption that the system is not deformed and the intermittent repetitive training of the memory unit are the essential characteristics of iterative learning control. The memory function of the repeated learning control is completed by the repeated controller, and its correction of the control effect is not realized intermittently but continuously.

Second, learning control based on neural reasoning. In a neural control system where the neural network directly acts as a controller, the neural network actually changes the connection weight between neurons in the network through a learning algorithm, thereby changing the non-linear mapping relationship between the input and output of the neural network, and gradually approaching the controlled dynamics. The inverse model of the process is used to achieve the task of control. This learning of neural networks is different from the learning forms in iterative learning control and repetitive learning control. The former study is based on the idea of approximation, while the latter uses the previous control experience of the control system to find an ideal input characteristic curve based on the actual output signal and the expected signal of the measurement system, so that the controlled object can produce the desired motion. The process of "finding" is the process of learning control.

Third, learning control based on pattern recognition. The first problem encountered when applying the principles and methods of pattern recognition to control systems is how to describe the dynamic characteristics of the controlled object. For controlled objects with a reference model, pattern recognition is mainly used as a signal processing method, but it has no practical value due to the large amount of calculation. For some complex production processes that cannot be modeled or parameter estimated, pattern recognition has become an important means to obtain working condition information and knowledge.

5. Conclusion and future prospects

In **Table 3**, we introduce the advantages and disadvantages of Artificial Neural Networks, Machine learning control, Bayesian probability control, Fuzzy control, Expert system and Genetic algorithm Control.

Advanced intelligent control is mainly used in comprehensive application scenarios such as computer technology, GPS positioning technology, or precision

Category	Description	Advantage	Disadvantage
Artificial Neural Networks [19, 20]	A mathematical or computational model that mimics the structure and function of a biological neural network and is used to estimate or approximate functions. In most cases, artificial neural networks can change the internal structure based on external information. It is an adaptive system, that is, it has learning functions.	(1) Non-linear, neural network can fully approximate any non-linear function in theory. (2) Parallel distributed processing, neural network has a high degree of parallel structure and parallel implementation capabilities, making it have a greater degree of fault tolerance and strong data processing capabilities. (3) Learning and self-adaptability can learn and remember the information provided by the knowledge environment. (4) Multi-variable processing. The neural network can naturally process multiple input signals and has multiple outputs. It is very suitable for multi-variable systems.	(1) The solution provided by the neural network is still a "black box". It can neither read out the appropriate cause for such a specific behavior, nor can it manually modify the neural network to change a specific expected behavior. (2) For most general mass-market products, the computing power of pure neural networks is limited. (3) Choosing the appropriate network model and set the parameters of the learning algorithm is still a "black art" and requires more experience.
Machine learning control [21, 22]	Machine learning control is programming computers to optimize a performance criterion using example data or past experience. The main applications are complex non-linear systems that are not suitable for control system methods.	(1) Very strong learning ability. (2) The neural network has many layers and a wide width, and can theoretically map to any function, so it can solve very complicated problems. (3) Highly dependent on data, the larger the amount of data, the better his performance. (4) There are many frameworks that can be used and portability is good.	(1) Large amount of calculation and high cost. Many applications are not suitable for use on mobile devices. (2) High computing power requirements. The mainstream computing power uses GPU and TPU, so the hardware requirements are high and the cost is high. (3) Model design is very complicated and requires a lot of human and material resources and time to develop new algorithms and models. (4) Because learning is dependent on data and is not highly interpretable. In the case of imbalanced training materials, problems such as gender discrimination and racial discrimination will occur, which is prone to bias.
Bayesian probability control [23, 24]	Bayesian probabilistic control should measure the confidence of an individual for an uncertain proposition and use this property to control it, so it is subjective in this sense. Using the probability theory proposed by Bayes, we can examine the sensitivity of decision-making. Bayes proposed the concepts of prior and posterior probability: the prior probability can be modified according to new information to obtain the posterior probability. Therefore, Bayesian theory is used to incorporate new information into analysis.	(1) The Bayesian model has stable classification efficiency. (2) It performs well on small-scale data, can handle multi-class tasks, and is suitable for incremental training, especially when the amount of data exceeds the memory, you can go for incremental training in batches. (3) Not very sensitive to missing data, and the algorithm is relatively simple, often used for text classification.	(1) Bayesian model has the smallest error rate compared with other classification methods. However, this is not always the case. This is because given the output category of the Naive Bayes model, the attributes are assumed to be independent of each other. This assumption is often not true in practical applications. When the correlation is large, the classification effect is not good. (2) You need to know the prior probability, and the prior probability often depends on the hypothesis. There can be many hypothetical models, so the prediction effect is not good due to the hypothetical prior model. (3) Since we determine the classification by using the prior and the data to determine the posterior, the classification decision has a certain error rate. (4) Very sensitive to the form of input data.

Category	Description	Advantage	Disadvantage
Fuzzy control [25, 26]	Computer intelligent control based on fuzzy set theory, fuzzy linguistic variables, and fuzzy logic reasoning. The input of this mechanism is to change the original 0 and 1 data into a value between 0 and 1 through fuzzification, which is closer to human thinking than the original nonzero or one dichotomy. In the process of inference, the data is fuzzy, but through the steps of defuzzification, the output can be made to an accurate value. Fuzzy control is often used in intelligent computing, expert system construction, and neural network-like applications.	(1) Fuzzy control is a rule-based control. It directly uses language-based control rules. The starting point is the control experience of field operators or the knowledge of relevant experts. It is not necessary to establish an accurate mathematical model of the controlled object in the design. Therefore, the control mechanism and strategy are easy to accept and understand, and the design is simple and easy to apply. (2) Starting from the qualitative understanding of industrial processes, it is relatively easy to establish language control rules, so fuzzy control is very suitable for those objects whose mathematical models are difficult to obtain, whose dynamic characteristics are not easy to grasp or whose changes are very significant. (3) Model-based control algorithms and system design methods can easily lead to large differences due to different starting points and performance indicators; but a system's language control rules are relatively independent. It is easy to use fuzzy connections between these control rules. Finding a compromise option makes the control effect better than conventional controllers. (4) Fuzzy control is designed based on heuristic knowledge and language decision rules, which is helpful for simulating the processes and methods of artificial control, enhancing the adaptive ability of the control system, and making it have a certain level of intelligence. (5) The robustness of the fuzzy control system is strong, and the influence of interference and parameter changes on the control effect is greatly reduced, which is especially suitable for the control of nonlinear, time-varying and purely lagging systems.	(1) The design of fuzzy control still lacks systematicness, which is difficult to control complex systems. So how to establish a system of fuzzy control theory to solve a series of problems such as the mechanism of fuzzy control, stability analysis, and systematic design methods. (2) How to obtain fuzzy rules and membership functions, that is, the design method of the system is currently based on experience. (3) Fuzzy processing of information will cause the control accuracy of the system to decrease and the dynamic quality to deteriorate. If you want to improve the accuracy, you will inevitably increase the number of quantization levels, which will lead to the expansion of the rule search range, reduce the speed of decision-making, and even fail to control in real time. (4) There is still room for discussion on how to ensure the stability of fuzzy control systems, that is, how to solve the problems of stability and robustness in fuzzy control.
Expert system [27]	This is a programming system with expert-level problem-solving capabilities in a specific field. It can effectively use the effective experience and expertise accumulated by experts for many years to solve problems that require experts to solve by simulating the expert's thinking process.	(1) The expert system can work efficiently, accurately, thoughtfully, quickly and tirelessly. (2) The expert system is not affected by the surrounding environment when solving practical problems, and it is impossible to forget and forget. (3) The expertise of experts can be freed from the constraints of time and space in order to promote valuable and scarce	(1) Its design cost and construction cost are extremely high, so it is rare in the industry today. (2) The ability to deal with common sense is low and the requirements for experts are very high. (3) There is still a need to develop deep inference systems. (4) The ability to interpret at different levels is poor. (5) It is difficult to make the

Category	Description	Advantage	Disadvantage
		expert knowledge and experience. (4) Expert systems can promote development in various fields. (5) Expert systems can bring together the knowledge and experience of experts in multiple fields and their ability to collaborate to solve major problems. (6) The level of military expert system is one of the important signs of national defense modernization. (7) The development and application of expert systems have huge economic and social benefits. (8) The research expert system can promote the development of the whole science and technology.	expert system have the ability to learn. (6) It is costly and difficult to achieve a decentralized expert system. (7) Poor ability to easily acquire and update knowledge.
Genetic algorithm control [28]	The genetic algorithm is a computational model that simulates Darwin's genetic selection and natural evolutionary biological evolution process. Its idea originates from the natural laws of biological genetics and survival of the fittest, and it is a search algorithm with an iterative process of "survival + detection". The genetic algorithm targets all individuals in a population, and uses randomization techniques to guide an efficient search of an encoded parameter space. Among them, selection, crossover and mutation constitute the genetic operation of the genetic algorithm; the five elements of parameter coding, initial population setting, fitness function design, genetic operation design, and control parameter setting constitute the core content of the genetic algorithm.	(1) produce interpretable results. (2) Results are easy to apply. (3) The range of data types that can be processed is extremely large. (4) Can be used for optimization. (5) Easy integration with neural network.	(1) Many problems have encoding difficulties. (2) No guarantee of optimization. (3) High computing cost. (4) Not many commercial software packages available.

Table 3.
Development trend of intelligent control technology.

sensing technology. With the increasingly fierce competition in the product market, intelligent products have obtained good application advantages in practical operations and applications. The main results include greatly improving the operator's operating efficiency, improving the quality of work in some dangerous places, and reducing work intensity, solving application of some dangerous and key constructions jobs, enhanced machine automation and intelligence, improved equipment reliability and reduced maintenance costs, and intelligent fault diagnosis, environmental protection and energy saving, etc.

According to the, the integration is shown in **Table 4** [29, 30].

Category	Item	Description
Performance development	High speed, high precision and high efficiency.	Speed, accuracy and efficiency are the key performance indicators of machinery manufacturing technology. Due to the use of high-speed CPU wafers, RISC wafers, multi-CPU control systems, and AC digital servo systems with high-resolution absolute detection elements, effective measures to improve the dynamic and static characteristics of the machine tools are also taken. Has been greatly improved.
	Flexible	It includes two aspects: the flexibility of the CNC system itself, the CNC system adopts a modular design, and the function coverage is large. Strong cutting ability, easy to meet the needs of different users; the flexibility of group pull system, the same group control system can automatically adjust the material flow and information flow according to the requirements of different production processes, so as to maximize the use of group control system efficacy.
	Process composite and multi-axis	Composite processing with the main purpose of reducing process and auxiliary time. It is developing in the direction of multi-axis and multi-series control functions. The process compounding of NC machine tools means that after the work piece is clamped on a machine tool at one time, the multi-process and multi-surface composite processing is completed through various measures such as automatic tool change, rotating spindle head or turntable.
	Real-time intelligence	Early real-time systems were usually aimed at relatively simple and ideal environments, and their role was to schedule tasks to ensure that tasks were completed within prescribed deadlines. Artificial intelligence attempts to implement various intelligent behaviors of humans with computational models. To date, science and technology have developed. Real-time systems and artificial intelligence are combined. Artificial intelligence is developing in a more realistic field with real-time response, and real-time systems are also developing in more complex applications with intelligent behavior. This has created a new field of real-time intelligent control.
Functional development	Graphical user interface	The user interface is the interface between the CNC and the user. Because different users have different requirements for the interface, the workload of developing the user interface is huge, and the user interface has become one of the most difficult parts in computer software development. Current Internet, virtual reality, scientific computing visualization, and multimedia technologies also place higher demands on user interfaces. The graphical user interface greatly facilitates the use of non-professional users. People can operate through windows and menus to facilitate the realization of blueprint programming and fast programming, 3D color stereo dynamic graphic display, graphic simulation, dynamic tracking and simulation of graphics, different directions of view and partial display scaling.
	Visualization of scientific computing	Visualization in scientific computing can be used to efficiently process and interpret data, so that information exchange is no longer limited to words and

Category	Item	Description
		language education, but visual information such as graphics, images, and animation can be used directly. The combination of visualization technology and virtual environment technology has further broadened the application fields, such as design without drawings, virtual prototype technology, etc., which is of great significance for shortening product design cycles, improving product quality, and reducing product costs. In the field of numerical control technology, visualization technology can be used for CAD / CAM, such as automatic programming and design, automatic parameter setting, dynamic processing and display of tool compensation and tool management data, and visual simulation of machining processes.
	Diversification of interpolation and compensation methods	Multiple interpolation methods such as linear interpolation, circular interpolation, cylindrical interpolation, spatial elliptical surface interpolation, thread interpolation, polar coordinate interpolation, 2D + 2 spiral interpolation, NANO interpolation, NURBS interpolation (non-uniform Rational B-spline interpolation), polynomial interpolation, etc. Various compensation functions such as clearance compensation, verticality compensation, quadrant error compensation, pitch and measurement system error compensation, speed-related feed forward compensation, temperature compensation, tool radius compensation with smooth approach and exit, and opposite point calculation.
	Built-in high-performance PLC	The high-performance PLC control module is built in the CNC system, which can be directly programmed with trapezoidal circles or high-level languages. It has intuitive online debugging and online help functions. The programming tool contains the real side of the standard PLC user program for lathe and milling machine. Edit and modify based on PLC user program, so as to create your own application program conveniently.
	Application of multimedia technology	Multimedia technology integrates computer, audio-visual, and communication technologies, so that the computer has the ability to comprehensively process sound, text, image and video information. In the field of CNC technology. The application of multimedia technology can achieve comprehensive and intelligent information processing, which has great application value in real-time monitoring systems and fault diagnosis of production field equipment and monitoring of production process parameters.
Architecture development	Integrated	Adopting highly integrated CPU, RISC wafers and large-scale programmable integrated circuits FPGA, EPLD, CPLD, and ASIC wafers for special integrated circuits, which can improve the integration of the CNC system and the speed of hardware and software. Applying LED flat panel display technology Improve display performance. Flat panel displays have the advantages of high technology content, light weight, small size, low power consumption, and easy portability. Achieve oversized display. Apply advanced packaging and interconnect technologies to integrate semiconductor and surface-mount technologies. By

Category	Item	Description
		increasing the density of integrated circuits, reducing the length and number of interconnects to reduce product prices, improve performance, reduce component size, and increase system reliability.
	Modular	The hardware modularity is easy to realize the integration and standardization of the numerical control system. According to different functional requirements, the basic modules, such as CPU, memory, position servo, PLC, input and output interface, and communication modules, are made into standard serial products. The building block method is used to cut functions and increase or decrease the number of modules to form different grades of CNC systems.
	Networking	Machine tool networking can perform remote control system and unmanned operation. Networking can program, set, operate and run other machine tools on any one machine tool. The pictures of different machine tools can be displayed on the screen of each machine at the same time.

Table 4.
Development trend of intelligent control technology.

At present, the neural fuzzy network has its input and output space divided into a checkerboard pattern. Although it is very easy to implement in hardware, as the input and output variables increase, the number of this checkerboard pattern increases. This leads to an unrealistic increase in the number of required memory or hardware, because more training data is needed for better spatial segmentation than the method in the learning process, otherwise insufficient learning will occur. In complex systems, in order to avoid an increase in the number of partitions, it is a research direction to find a more flexible and irregular partitioning method. The implementation of fuzzy controllers with neural networks such as learning capabilities has become a very interesting research area in recent years. However, many neural fuzzy networks with learning capabilities often require expert knowledge before application. In order to improve its performance, it is also the research direction to automatically generate fuzzy rules and adjust the attribution function only from the training data. In recent years, because genetic algorithms have global optimization capabilities, genetic algorithms have become another useful tool. Currently, genetic algorithms are used to adjust the fuzzy controller's attribution function and neural network-like weighting values. The combination of genetic algorithms and neural-like fuzzy networks to accelerate their learning speed is also worth exploring.

Other intelligent control methods such as machine learning control, Bayesian probability control, expert system and genetic algorithm control, etc., or the aforementioned artificial neural networks and fuzzy control, will be from communication technology, manufacturing technology, construction technology, transportation technology and the integration of energy technology and other different levels is also an important task for us to continue to make good use of the advantages of intelligent control methods and eliminate the disadvantages in the future.

Author details

Kuo-Chi Chang[1]*, Kai-Chun Chu[1], Yuh-Chung Lin[1] and Jeng-Shyang Pan[2]

1 Fujian University of Technology, China

2 Shandong University of Science and Technology, China

*Address all correspondence to: albertchangxuite@gmail.com

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