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Novel Yinger Learning Variable Universe Fuzzy Controller

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Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/48266>

1. Introduction

Fuzzy control is a practical alternative for a variety of challenging of challenging control applications because it provides a convenient method for constructing nonlinear controllers via the use of heuristic information. The heuristic information may come from an operator who has acted as a human controller for a process. In the fuzzy control design methodology, a set of rules are written down by the operator on how to control the process, then make these into a fuzzy controller that emulates the decision-making process of the human. In some cases, the heuristic information may come from other novel intelligent applications. In other cases, the heuristic information may come from a control engineer who has performed extensive mathematical modeling, analysis, and development of control algorithms for a particular process. Regardless of where the heuristic control knowledge comes from, fuzzy control provides a user-friendly formalism for representing and implementing the ideas.

Over the past few decades, fuzzy logic theory is widely used: process control, management and decision making, operations research, economies. Dealing with simple 'yes' and 'no' answers is no longer satisfactory enough; a degree of membership (Zadeh, 1965) became a new way of solving problems. Fuzzy logic derives from the truth that the human common sense reasoning mode is approximate in nature.

In this chapter we provide a control engineering perspective on novel fuzzy controller. We take a pragmatic engineering approach to the design, analysis, performance evaluation, and implement of fuzzy control system. The chapter is basically broken into five parts. In section 2, we provide an overview of conventional control system design. In section 3 the basic theories of variable universe fuzzy control are been introduced. In section 4, we cover the novel fuzzy controller based on Yinger algorithm. In section 5, we use some examples to show how to design, simulate, and implement these controllers. Finally, in section 6, we

explain how to write a computer program to simulate the novel fuzzy control system, using either a high-level language or Matlab.

2. Conventional control system design

2.1. Introduction

A control system is a device, or set of devices to manage, command, direct or regulate the behavior of other devices or system. There are two common classes of control systems, with many variations and combinations: logic or sequential controls, and feedback or linear controls. There is also fuzzy logic, which attempts to combine some of the design simplicity of logic with the utility of linear control. Some devices or systems are inherently not controllable. A basic control system is shown in figure 1. The plant is object to be controlled. Its inputs are $u(t)$, its outputs are $y(t)$, and reference input is $r(t)$.

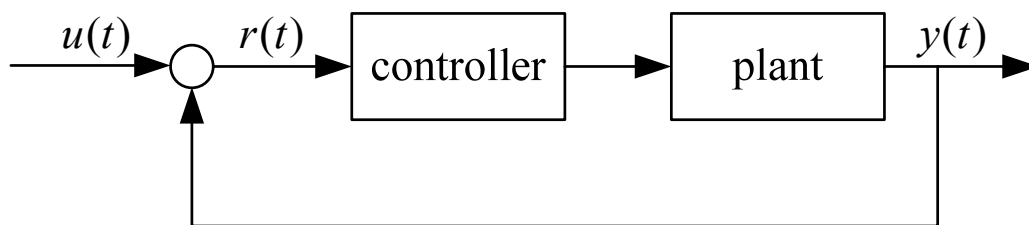


Figure 1. Control system

2.2. Mathematical modeling

The mathematical model is a description of a system using mathematical concepts and language. The process of developing a mathematical model is termed mathematical modeling. Mathematical models are used not only in the natural sciences (such as physics, biology, earth science, meteorology) and engineering disciplines (such as computer science, artificial intelligence), but also in the social sciences (such as economics, psychology, sociology and political science), physicists, engineers, statisticians, operations research analysts and economists use mathematical models most extensively. A model may help to explain a system and to study the effects of different components, and to make predictions about behaviour.

Mathematical models can take many forms, including but not limited to dynamical systems, statistical models, differential equations, or game theoretic models. These and other types of models can overlap, with a given model involving a variety of abstract structures. In general, mathematical models may include logical models, as far as logic is taken as a part of mathematics. In many cases, the quality of a scientific field depends on how well the mathematical models developed on the theoretical side agree with results of repeatable experiments. Lack of agreement between theoretical mathematical models and experimental measurements often leads to important advances as better theories are developed.

When a control engineer is given a control problem, often one of the first tasks is the development of a mathematical model of the process to be controlled, in order to gain a clear understanding of the problem. Basically, there are only a few ways to actually generate the model. We can use first principles of physics to write down a model. Another way is to perform "system identification" via the use of real plant data to produce a model of the system. Sometimes a combined approach is used where we use physics to write down a general different equation that we believe represent the plant behavior, and then we perform experiments on the plant to determine certain model parameters or functions.

Often, more than one mathematical model is produced. A "truth model" is one that is developed to be as accurate as possible so that it can be used in simulation-based evaluations of control systems. It must be understood, however, that there is never a perfect mathematical model for the plant. The mathematical model is an abstraction and hence cannot perfectly represent all possible dynamics of any physical process. This is not to say that we cannot produce models that are "accurate enough" to closely represent the behavior of a physical system. Usually, control engineer to be able to design a controller that will work. Then, they often also need a very accurate model to test the controller in simulation before it is tested in an experimental setting. Hence, lower-order "design model" are also often developed that may satisfy certain assumption yet still capture the essential plant behavior. Indeed, it is quite an art to produce good low-order model that satisfy these constraints. We emphasize that the reason we often need simpler models is that the synthesis techniques for controller often require that the model of the plant satisfy certain assumptions or there methods generally cannot be used.

Linear models such as the one in Equation (1) have been used extensively in the past and the control theory for linear system is quite mature.

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx + Du\end{aligned}\tag{1}$$

In this case u is the m -dimensional input; x is the n -dimensional state; y is the p -dimensional output; and A, B, C and D are matrices of appropriate dimension. Such models are appropriate for use with frequency domain design techniques, the root-locus method, state-space methods, and so on. Sometimes it is assumed that the parameters of the linear model are constant but unknown, or can be perturbed from their nominal values.

Much of the current focus in control is on the development of controllers using nonlinear models of the plant of the form

$$\begin{aligned}\dot{x} &= f(x, u) \\ y &= g(x, u)\end{aligned}\tag{2}$$

Where the variables are defined as for the linear model and f and g are nonlinear functions of their arguments. One form of the nonlinear model that has received significant attention is

$$\dot{x} = f(x) + g(x)u \quad (3)$$

Since it is possible to exploit the structure of this model to construct nonlinear controllers. Of particular with both of the above nonlinear models is the case where f and g are not completely known and subsequent research focuses on robust control of nonlinear system.

Discrete time versions of the above models are also used, and stochastic effect are often taken into account via the addition of a input or other stochastic effects. Under certain assumptions you can linearize the nonlinear model in Equation(2) to obtain a linear one. In this case we sometimes think of the nonlinear model as the truth model, and the linear model that are generated from it as control design model.

There are certain properties of the plant that the control engineer often seeks to identify early in the design process. For instance, the stability of the plant may be analyzed. The effects of certain nonlinearities are also studied. The engineer may want to determine if the plant is controllable to see, for example, if the control input will be able to properly affect the plant; and observable to see, for example, if the chosen sensors will allow the controller observe the critical plant behavior so that it can be compensated. Overall, this analysis of the plant's behavior gives the control engineer a fundamental understanding of the plant dynamics.

2.3. Performance objectives and design constraints

Controller design entails constructing a controller to meet the specifications. Often the first issue to address is whether to use open or closed-loop control. Often, need to pay for a sensor for the feedback information and there need to justification for this cost. Moreover, feedback can destabilize the system. Do not develop a feedback controller just because you are used to developing feedback controllers; you may want to consider an open-loop controllers since it may provide adequate performance. Assuming you use feedback control, the closed-loop specifications can involve the following factors: Disturbance rejection properties; Insensitivity to plant parameter variations; Stability; Rise-time.

2.4. Controller design

Conventional control has provided numerous methods for controllers for dynamic system. Some of there are listed below:

1. Proportional-integral-derivative(PID) control: Over 90% of the controllers in operation today are PID controllers. This approach is often viewed as simple, reliable, and easy to understand. Often, like fuzzy controller, heuristics are used to tune PID controllers.
2. State-space methods: State feedback, observers, and so on.
3. Optimal control: Linear quadratic regulator, use of Pontryagin's minimum principle or dynamic programming, and so on.
4. Nonlinear methods: Feedback linearization, Lyapunov redesign, sliding mode control, backstepping, and so on.
5. Adaptive control; model reference adaptive control, self-tuning regulators, nonlinear adaptive control, and so on.

Basically, there conventional approaches to control system design offer a variety of ways to utilize information from mathematical model on how to do good control. Sometimes they do not take into account certain heuristic information early in the design process, but use heuristics when the controller is implemented to tune it (tuning is invariably needed since the model used for the controller development is not perfectly accurate). Unfortunately, when using some approaches to conventional control, some engineers become somewhat removed from the control problem, and sometimes this leads to the development of unrealistic control laws. Sometimes in conventional control, useful heuristics are ignored because they do not fit into the proper mathematical framework, and this can cause problem.

2.5. Performance evaluation

The next step in the design process is to perform analysis and performance evaluation. Basically, we need performance evaluation to test that we design does in fact meet the closed-loop specifications. This can be particularly important in safety-critical applications such as the control of a washing machine or an electric shaver, it may not be as important in the sense that failures will not imply the loss of life, so some of the rigorous evaluation methods can sometimes be ignored. Basically, there are three general ways to verify that a control system is operating properly: (1) mathematical analysis based on the use of formal models, (2) simulation-based analysis that most often uses formal models, and (3) experimental investigations on the real system.

3. Variable fuzzy control system design

The fuzzy controller block diagram is given in figure 2. The plant outputs are denoted by $y(t)$, its input is denoted by $u(t)$, and the reference input to the fuzzy controller is denoted by $r(t)$.

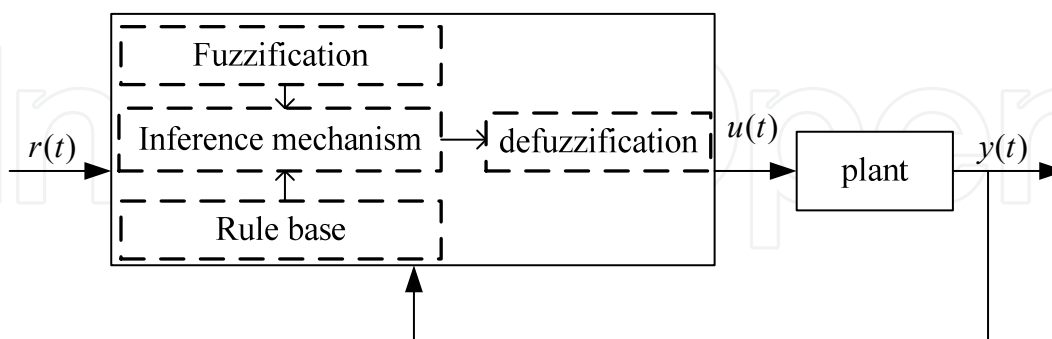


Figure 2. Fuzzy controller architecture

3.1. Fuzzy controller

Basically, the difficult task of modeling and simulating complex real-world systems for controller systems development, especially when implementation issues are considered, is

well documented. Even if a relatively accurate model of a dynamic system can be developed, it is often too complex to use require restrictive assumptions for the plant. It is for this reason that in practice conventional controllers are often developed via simple models of the plant behavior that satisfy the necessary assumptions, and via the ad hoc tuning of relatively simple linear or nonlinear controllers. Regardless, it is well understood.

Fuzzy control provides a formal methodology for representing, manipulating, and implementing a human's heuristic knowledge about how to control a system.

The fuzzy controller block diagram is given in Figure 2, where we show a fuzzy controller embedded in a closed-loop control system. The plant outputs are denoted by $y(t)$, its inputs are denoted by $u(t)$, and the reference input to the fuzzy controller is denoted by $r(t)$.

The fuzzy controller has four main components: (1) The "rule-base" holds the knowledge, in the form of a set of rules are relevant at the current time and then decides what the input to the plant should be, (3) The fuzzification interface simply modifies the inputs so that they can be interpreted and compared to the rules in the rule-base. And (4) the defuzzification interface converts the conclusions reached by the inference mechanism into the inputs to the plant.

To design the fuzzy controller, the control engineer must gather information on how the artificial decision maker should act in the closed-loop system. Sometimes this information can come from a human decision maker who performs the control task, while at other times the control engineer can come to understand the plant dynamics and write down a set of rules about how to control the system without outside help. These "rules" basically say, "If should be some value." A whole set of such "If-Then" rules is loaded into the rule-base, and specifications are met.

3.2. Structure of variable adaptive fuzzy controller

Let $X_i = [-E, E]$ ($i = 1, 2, \dots, n$) be the universe of input variable x_i ($i = 1, 2, \dots, n$), and $Y = [-U, U]$ be the universe of output variable y . $\mu_i = \{A_{ij}\}_{(1 \leq j \leq m)}$ stands for a fuzzy partition on X_i , and $B = \{B_j\}_{(1 \leq j \leq m)}$ defines a fuzzy partition on Y . A group of fuzzy inference rules is formed as follow:

If x_1 is A_{1j} and x_2 is A_{2j} and...and x_n is A_{nj} then y is B_j , $j = 1, 2, \dots, m$

The fuzzy logic system can be represented as an n -dimension piecewise interpolation function $F(x, x_2, \dots, x_n)$:

$$F(x, x_2, \dots, x_n) = y(x, x_2, \dots, x_n) = \sum_{j=1}^m \prod_{i=1}^n A_{ij}(x_i) y_j \quad (4)$$

Generally speaking, a function $\alpha : X \rightarrow [0, 1], x \rightarrow \alpha(x)$ can be called a contraction-expansion factor on $X_i = [-E, E]$. The so-called variable universe means X_i and Y can change with changing variable x_i and y expressed by:

$$X_i(x_i) = [-\alpha(x_i)E_i, \alpha(x_i)E_i] \quad (5)$$

$$Y(y) = [-\beta(y)U, \beta(y)U] \quad (6)$$

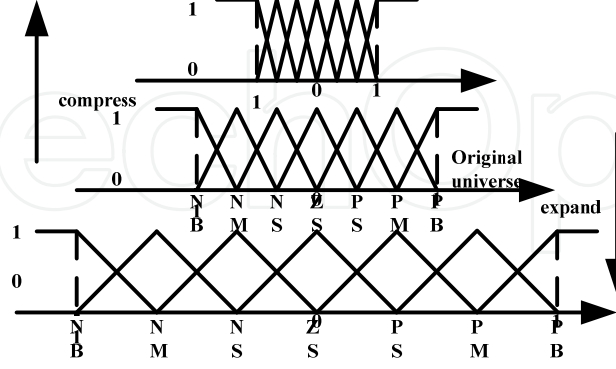


Figure 3. Universe compress and expand

4. Novel fuzzy controller based on Yinger algorithm

Novel fuzzy controller is composed of three parts. Firstly, new kind of contraction-expansion factor is established, then local space is optimized, finally novel controller dynamically adjust output by rules.

4.1. Optimal local spaces

Many real-world environments in which learning systems have to operate are time-varying. Several aspects of the learning problem can vary, including the mapping to be learned, and the sampling distribution that governs the input-space location of exemplars that make up the input information. In this section, K-Vector Nearest Neighbors (K-VNN) is proposed to this problem.

Define 1. Lets Ω_k is input sets which can be defined to local space as:

$$\Omega_k \equiv \{X_1, \dots, X_K\} = \{X_i | D(X_i, X_m) < h\} \quad (7)$$

Where h is radius of local space (Ω_k), and data-window is changed by adjusting it. $D(A, B)$ is the distance function which is defined by (8), X_1, \dots, X_K are messages to input.

Define 2. Lets $A = [A_1, \dots, A_n]$ and $B = [B_1, \dots, B_n]$, in the Euclidean space, gets distance and intersection angle:

$$\begin{cases} d(A, B) = \sqrt{\|A - B\|_2} \\ \theta(A, B) = \arccos \frac{A^T B}{\|A\|_2 \cdot \|B\|_2} \end{cases} \quad (8)$$

According to (7), we can get the distance and intersection angle of X_i and X_d , from input-output specimen choice similar message to Ω_k .

If intersection angle of X_i and X_d greater than 90° , thinking X_i stray from X_d , and define as follows:

$$D(X_i, X_d) = ae^{[-d(X_i, X_d)]} + b \sin[\varphi(X_i, X_d)] \quad (9)$$

$$(0 \leq a \leq 1/2, 0 \leq b \leq 1/2)$$

From (9), we can see, if X_i is more similar to X_d , $e^{[-d(X_i, X_d)]}$ and $\sin[\varphi(X_i, X_d)]$ are more similar to 1, use this method and get the new input set

$$\Omega_k = \{(X_1, Y_1), \dots, (X_K, Y_K) | D(X_1, X_d) > \dots > D(X_K, X_d)\} \quad (10)$$

From this section, some noise can be deleted by this section.

4.2. Contraction-expansion factor

Now the popular contraction-expansion factor is $\alpha(x) = 1 - ce^{(-kx^2)}$ ($c \in (0, 1)$ $k \geq 0$), but the algorithm module can not be realized easily by C++ which support some methods by using VC++ accomplish control system. So building up a kind of contraction-expansion factor to nonlinear system is very important.

1. Establish differential equation

Firstly, $\alpha(e(t))$ is strictly monotonously increasing on $[0, 1]$ and monotonously decreasing on $[-1, 0]$.

Secondly, $e(t) \rightarrow 0$ Then $\alpha(e(t)) \rightarrow \varepsilon = 0.0001$ and $|e(t)| \rightarrow 1$ then $\alpha(e(t)) \rightarrow 1$.

Thirdly, $\Delta\alpha(e(t)) = k\Delta e(t)$, and to the same $\Delta e(t)$, $e(t)$ is larger and $\Delta\alpha(e(t))$ is larger too. From those conditions the differential equation can be build as follow:

$$\Delta\alpha(e(t)) = ke(t)\Delta e(t)(E - e^2(t)) \quad (11)$$

get hold of:

$$\alpha(x) = -\frac{1}{4}kx^4 + \frac{E}{2}kx^2 + c \quad (12)$$

and initialized condition:

when $e(t) = 0$ then $\alpha(e(t)) = D(X_i, X_d)$, and $|e(t)| = E$ $\alpha(e(t)) = 1$

get hold of:

$$\alpha(x) = -\frac{1}{4}kx^4 + \frac{E}{2}kx^2 + D(X_i, X_d) \quad (13)$$

2. Analyze and verify characters

1. Duality $\forall e(t) \in E \quad \alpha(e(t)) = \alpha(-e(t))$
2. Near zero $\alpha(0) = D(X_i, X_d) > 0$
3. Monotonicity: $\forall e(t_1), e(t_2) \in [0, E]$ if $e(t_1) \geq e(t_2)$ then $\alpha(e(t_1)) \geq \alpha(e(t_2))$
4. Normality $\alpha(E) = \alpha(-E) = 1$

$$\alpha(x) = -\frac{1}{4}kx^4 + \frac{E}{2}kx^2 + D(X_i, X_d)$$

is the primary function can easily realize in nonlinear system. So the new kind of contraction-expansion factor is satisfied with the requests.

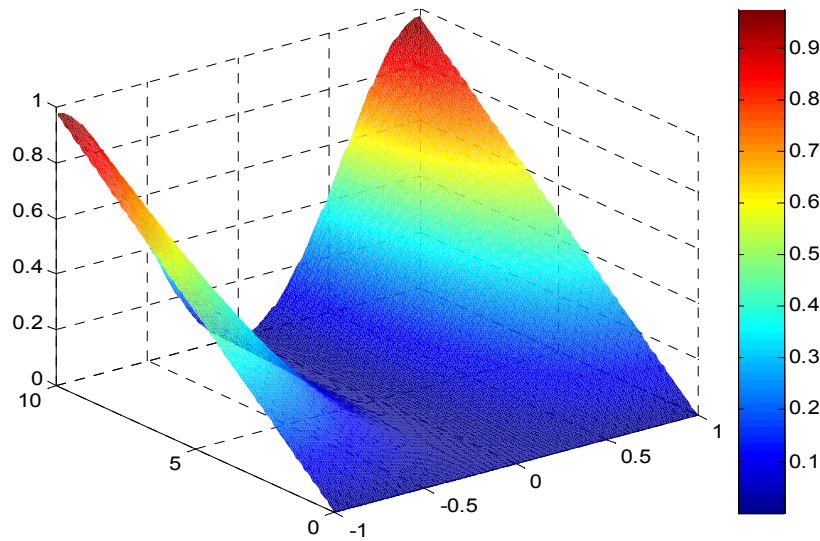


Figure 4. Function cluster surface ($k>0$)

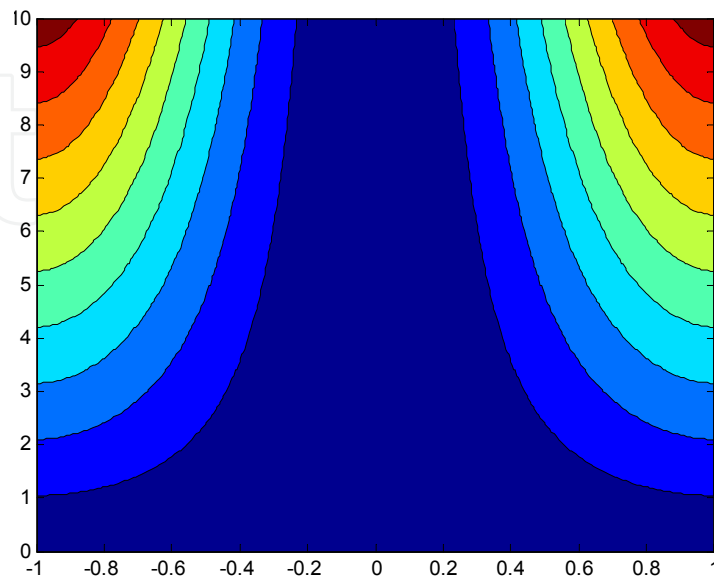


Figure 5. Function cluster surface contour($k>0$)

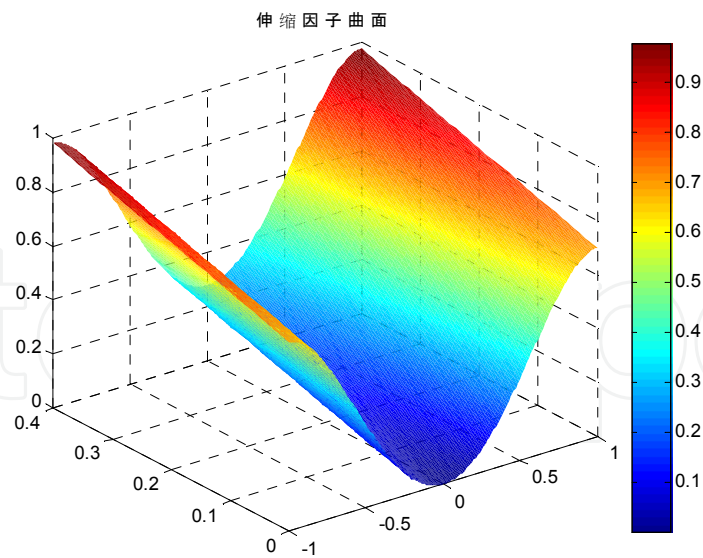


Figure 6. Function cluster surface ($c < 1$)

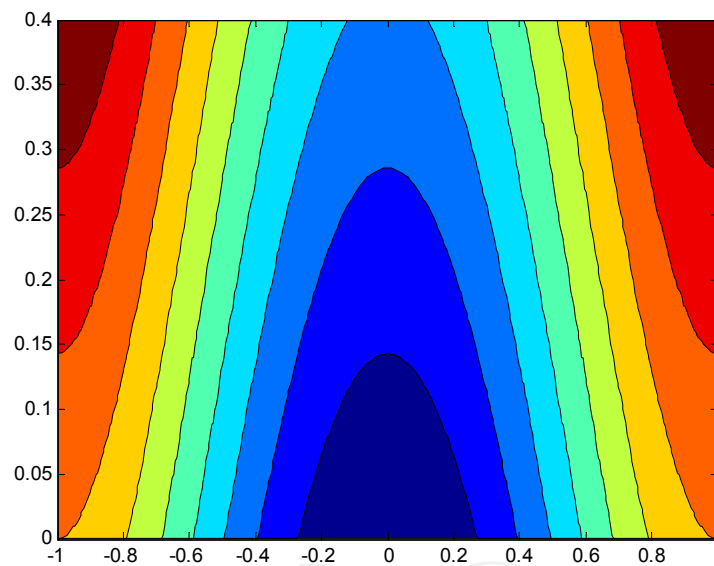


Figure 7. Function cluster surface contour ($c < 1$)

5. Examples

Choose the typical non-linear system to the new algorithm.

$$\text{Plant: } \begin{aligned} \dot{x}(t) &= \frac{1 - e^{-x(t)}}{1 + e^{-x(t)}} + u(t) \\ y(t) &= x(t) \end{aligned} \quad (14)$$

$$\lim_{t \rightarrow \infty} \|e(t)\| = \lim_{t \rightarrow \infty} \|r(t) - y(t)\| = 0 \quad (15)$$

$$\text{And } u(t) = u_c(t)$$

$$U[-1,1]$$

We can get the rules as follows:

if e is Nb then u is NB, if e is Nm then u is NM

if e is Ns then u is NS, if e is Pb then u is PB

if e is Pm then u is PM, if e is Ps then u is PS

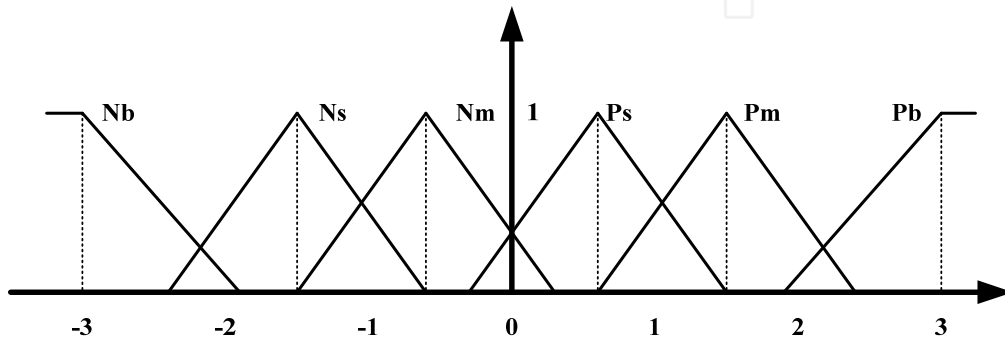


Figure 8. Function

$$Nb(e) = \begin{cases} 1, & e \leq -3 \\ \frac{e+1.9}{-1.1}, & -3 \leq e \leq -1.9 \\ 0, & \text{etc} \end{cases} \quad Nm(e) = \begin{cases} \frac{e+2.4}{0.9}, & -2.4 \leq e \leq -1.5 \\ \frac{e+0.6}{-0.9}, & -1.5 \leq e \leq -0.6 \\ 0, & \text{etc} \end{cases}$$

$$Ns(e) = \begin{cases} \frac{e+1.5}{0.9}, & -1.5 \leq e \leq -0.6 \\ \frac{e}{-0.6}, & -0.6 \leq e \leq 0 \\ 0, & \text{etc} \end{cases} \quad Ps(e) = \begin{cases} \frac{e}{0.6}, & 0 \leq e \leq 0.6 \\ \frac{e-1.5}{-0.9}, & 0.6 \leq e \leq 1.5 \\ 0, & \text{etc} \end{cases}$$

$$Pm(e) = \begin{cases} \frac{e-0.6}{0.9}, & 0.6 \leq e \leq 1.5 \\ \frac{e-2.4}{-0.9}, & 1.5 \leq e \leq 2.4 \\ 0, & \text{etc} \end{cases} \quad Pb(e) = \begin{cases} 1, & e \geq 3 \\ \frac{e-1.9}{1.1}, & 1.9 \leq e \leq 3 \\ 0, & \text{etc} \end{cases}$$

$$y_1 = -1, y_2 = -0.5, y_3 = -0.2, y_4 = 0.2, y_5 = 0.5, y_6 = 1$$

$$u_c(t) = \beta(t)U \sum_{j=1}^m \prod_{i=1}^n A_{ij} \left(\frac{e(t)}{\alpha(e(t))} \right) y_j$$

$$\text{make } \alpha(e(t)) = -\frac{1}{81}e(t)^4 + \frac{2}{9}e(t)^2 + 0.0001$$

$$\text{and } \lim_{t \rightarrow \infty} \|e(t)\| = 0, P_n = (p_1, p_2, \dots, p_n)^T$$

$$\text{then } \beta'(t) = K \sum_{i=1}^n p_i e_i(t)$$

$$\beta(0) = 1, P_n|_{n=1} = p_1 = 1, k = 2, U = 3$$

$$u_c(t) = \beta(t)U \sum_{j=1}^m \prod_{i=1}^n A_{ij} \left(\frac{e(t)}{\alpha(e(t))} \right) y_j$$

$$u_c(t) = \beta(t)U \sum_{j=1}^m \prod_{i=1}^n A_{ij} \left(\frac{e(t)}{\alpha(e(t))} \right) y_j$$

$$= (k \int_0^t e^\tau(t) P_n dt + \beta(0)) U \sum_{j=1}^m \prod_{i=1}^n A_{ij} \left(\frac{e(t)}{\alpha(e(t))} \right) y_j$$

$$= 6 \left(\int_0^t e(t) dt + 1 \right) [-Nb(e'(t)) - 0.5Nm(e'(t)) - 0.2Ns(e'(t)) + 0.2Ps(e'(t)) + 0.5Pm(e'(t)) + Pb(e'(t))]$$

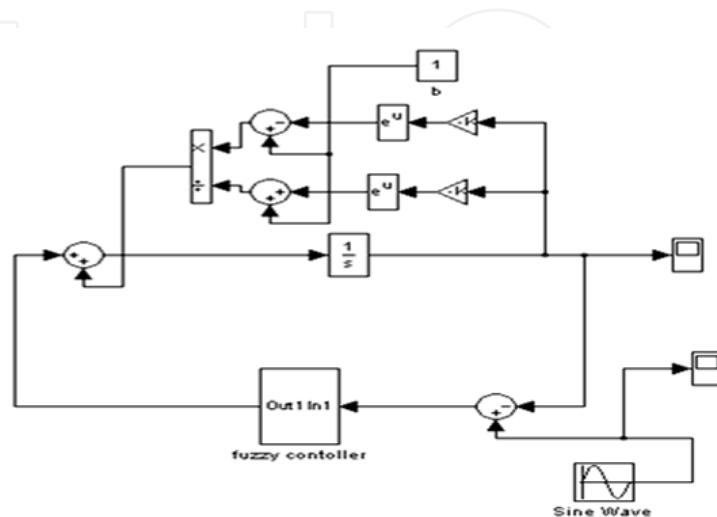


Figure 9. Controller

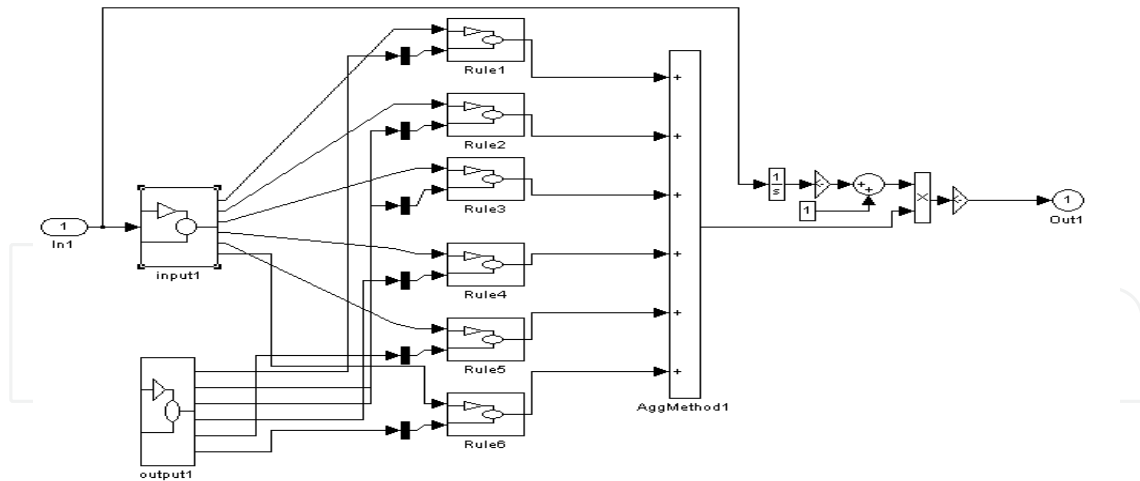


Figure 10. Rules

In order to make out the advantages of the new function, Let $r(t) = \sin t$ the result of controller (see Fig.11) is formed as follows

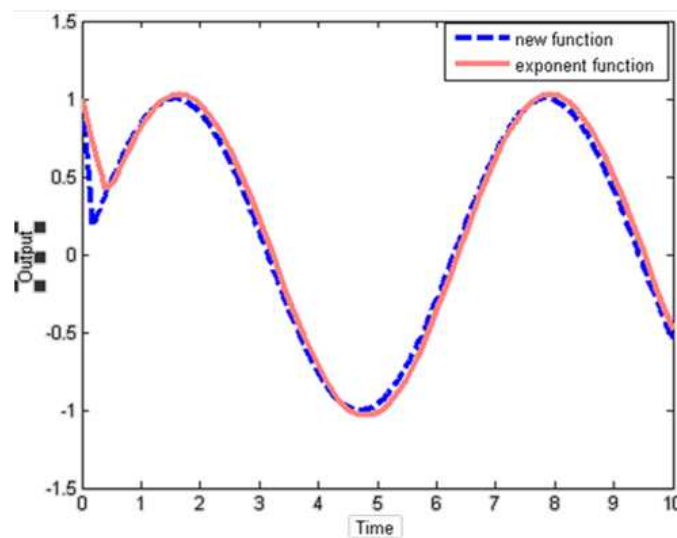


Figure 11. The contrast of control effect

Let

$$r(t) = \begin{cases} 1.5 & 0 \leq t \leq 3 \text{ and } 6 \leq t \leq 9 \\ 0.5 & \text{etc} \end{cases}$$

the result of control (see Fig.12 and Fig.13) is formed as follow

From Fig.12, we learn that there are some errors between aim curve (blue) and real curve (black) because of $\alpha(e(t)) = 1$. System cannot immediately regulate control strategy to make $e(t) = 0$. From Fig.13, we can clearly learn that the real curve (black) almost coincide with aim curve (blue). So we say that the variable fuzzy controller is one of the efficient tools for control system. From Fig.11, we can see the difference between the new function and exponential

function (conventional function), and the algorithm module with new contraction-expansion factor is applied successfully in Matlab, whose results show that algorithm module is reasonable, adaptive and feasible. In the other hand, the new function can be realized easily by C++ to optimize the controller of complicated nonlinear control system.

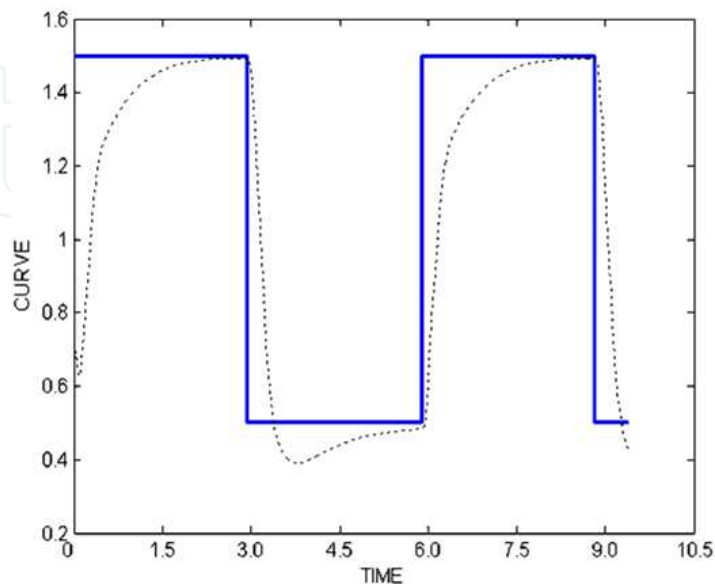


Figure 12. The simulation curves ($\alpha(e(t)) = 1$)

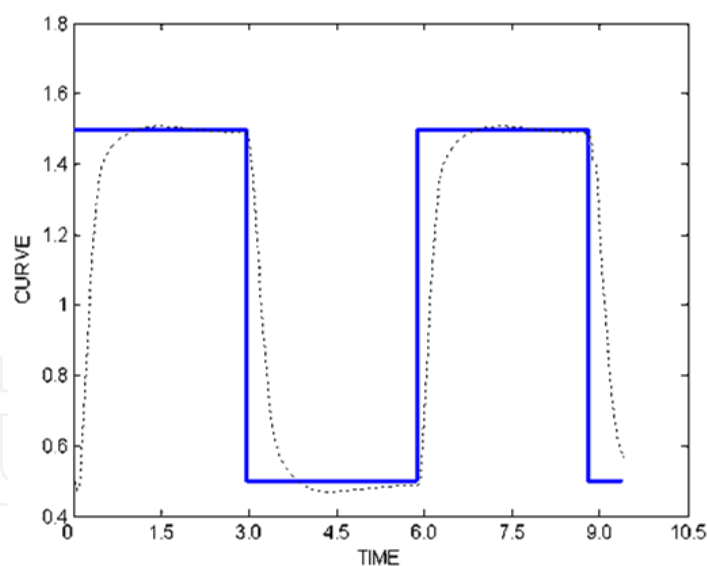


Figure 13. The simulation curves ($T=10$)

6. Practical application

Refrigerator is one kind of popular home appliance, and it became more and more important to economize the energy. The controller of conventional refrigerator keep anticipative temperature through PTC-relays and compress, but a lot of energy is waste. In this paper the new controller based on variable universe adaptive fuzzy control theory can

resolve this problem. The variable universe fuzzy control theory has become more and more important in process control. The idea of variable universe fuzzy control is first proposed in refs, and several types of variable universe adaptive fuzzy controller are discussed in ref.

The compressor, condenser, evaporator, capillary and other electro-equipments compose the refrigeration system which is a close circulatory system. R-600a as refrigeration material from the low-pressure liquid to gaseity in evaporator to make the icebox inside temperature lowed through absorbing the heat. In other words, the control system of refrigeration makes R-600a changed by electric power. The simplified model of the refrigerator (see Fig.14) show as follow:

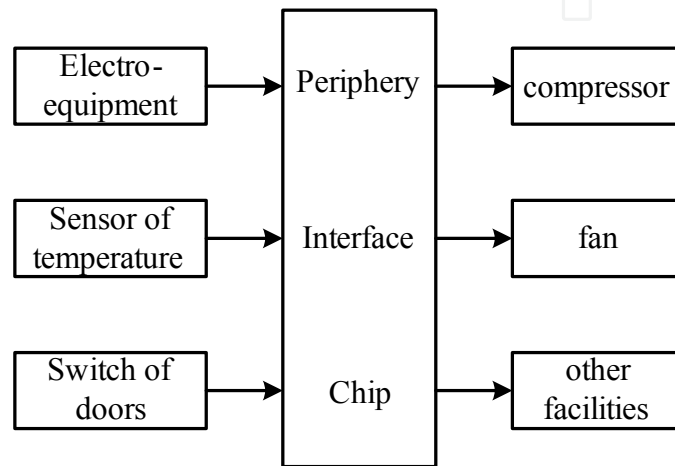


Figure 14. Simplified model of the refrigerator

The popular refrigerator through driving compressor makes the temperature constant, but there are some disadvantages in the control strategy. If there is minuteness temperature warp in system, control system frequent start-up equipments to modulate inside temperature, and a lot of energy will be wasted. In order to solve this problem, we design the new control strategy based on the idea of variable universe fuzzy control.

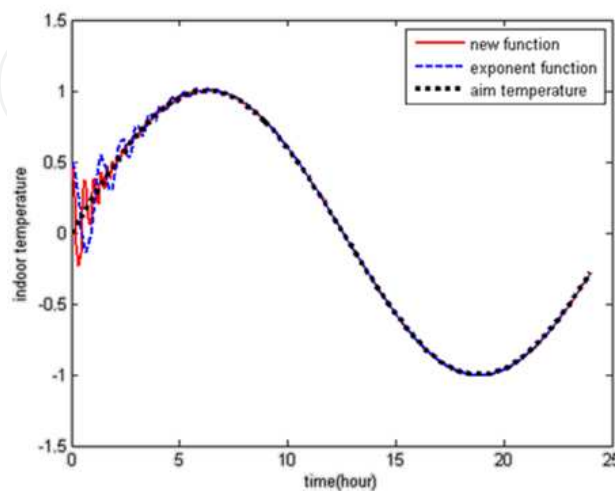


Figure 15. Contrast of controller effect

A refrigerator plant is a complex nonlinear system and may be prone to instability and oscillatory behaviors. The Fig.15 is the contrast of controller effect by Ying learning (red line), exponent function (blue line). In this section, a fuzzy controller is designed and simulated exclusively to control a refrigerator plant with a new-type function of contraction-expansion factor to optimize the controller of temperature is steady.

Using control method to explain medical phenomenon is currently a hot subject of research. The traditional Chinese drug fumigation steaming treat protrusion of protrusion of protrusion of lumbar intervertebral disc with steam generated by boiling medicinal herbs, and this process is a typical non-linear, multivariable, and strong coupling. Experienced nurse and doctor cure patient by their experience. So establish a model of this process can discover more factor of the disease, better treat to protrusion of protrusion of protrusion of lumbar intervertebral disc and reduce of energy consumption.

The traditional Chinese drug fumigation fume or steaming treat diseases with fume in moxibustion or with steam generated by boiling medicinal herbs, and its process is a typical non-linear, multivariable, strong coupling. In addition, its characters are difficult to quantitative analysis. So the period of treatment is only determined by experience of doctors. Therefore, there is theoretical and practical significance in studying of traditional Chinese drug fumigation medical data mining.

The illustration of the traditional Chinese drug fumigation machine is shown in Fig.16. Here, the type of machine is MJD-2003 and it has been used 6 years.

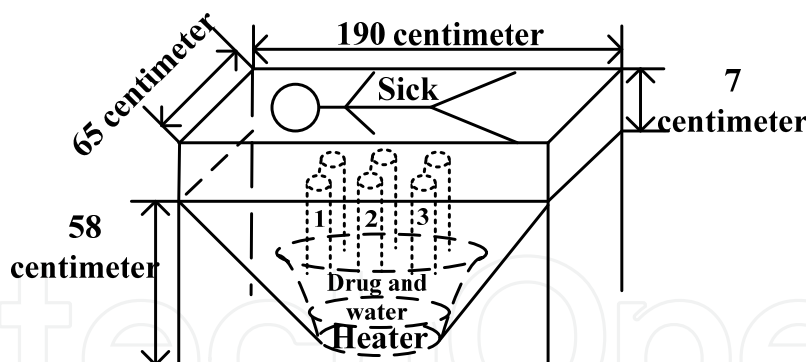


Figure 16. Drug Fumigation Machine

Doctor treats protrusion of Protrusion of protrusion of lumbar intervertebral disc with steam generated by boiling medicinal herbs at this machine.

Fig.17 is the temperature of steam to body by VUF and YL-VUF. YL-VUF is the blue real line, and VUF is the green dash line. In this picture the aim is 40 Celsius Degrees. The temperature decrease when patient's posture is changed. After 10.725 minute, YL-VUF makes the temperature to 40 Celsius Degrees. On the other hand, VUF almost cost 22.568 minute. DFNN and YL-VUF have the similar frame, but YL-VUF using new local space to forecast. So YL-VUF can avoid over heat.

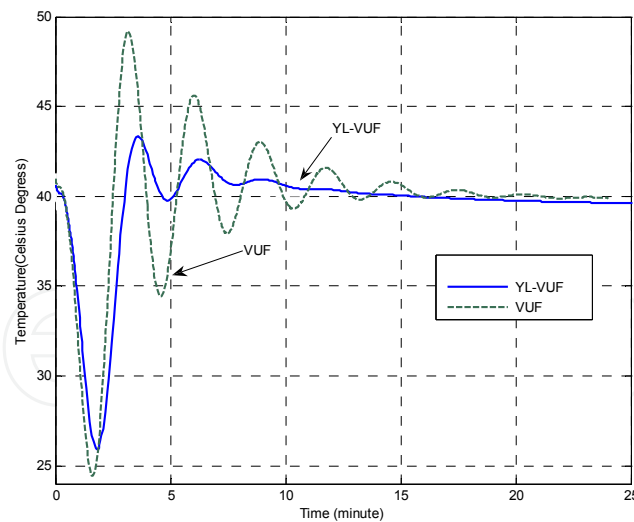


Figure 17. Temperature (YL-VUF and VUF) of steam to body

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