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Monitoring and Control of Anesthesia Using Multivariable Self-Organizing Fuzzy Logic Structure

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Summary. In this chapter, the design and implementation of Self-Organizing Fuzzy Logic Controller (SOFLC) is explored with a particular application to control a multivariable model of anesthesia. A concept called decomposition of multivariable self-organizing fuzzy logic structure is proposed in this chapter. Hence, the basic forms of a simple 2 terms SOFLC to a multi-term complex multi-input/multi-output (MIMO) controller will be presented. Different design strategies of MIMO will be outlined and the application of SOFLC systems to muscle relaxation and depth of anesthesia control will be explored in the simulations. After comparison with four different MIMO controllers, the successful simulation results have given confidence to perform on-line clinical trials at the operating theatre in the near future.

14.1 Introduction

Control of non-linear systems has grown rapidly due to the fact that most systems are inherently non-linear, moreover, linear control systems can only perform well on a linearized model of the process around the operating points. Most controllers such as a PID three term controllers, Model-Based Predictive Control (MBPC) and robust control (H_α) can do very well on a fixed set point. However, in recent years, there has been a move towards intelligent control with a qualitative dimension due to the widespread dissatisfaction with quantitative systems engineering. One of the main attractions of intelligent system design is the possibility of multivariable control system without the need for extensive dynamic models of the process [11, 25]. The main difficulty in the multivariable case is the interaction between variables together with sensitivity to faults in various channels. Intelligent systems, such as Neural Networks (NN), Fuzzy Logic Control (FLC), and Genetic Algorithms (GA), have been at the forefront

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of such methodologies and have proved to be strong contenders for other forms of control [8].

The application of intelligent control to medical systems has been around for many years [5, 14, 19], but due to the nature of the humans, differences from one person to another, the dynamic changes in the human response to external stimuli's and the effect of the different drugs on patients, a form of an adaptable intelligent controller can fix the description very well. An attractive approach to solving these problems is provided by the self-organizing fuzzy logic controller (SOFLC), which was first proposed by Procyk and Mamdani [26]. By mimicking the human learning process, the SOFLC has a learning algorithm and is capable of generating and modifying control rules according to an evaluation of the system's performance. There have been many studies and applications of SOFLC in recent years, but only a few in biomedical systems. Linkens and Hasnain [15] published an early study on SOFLC of muscle relaxation, but only in computer simulations. Recently, this has been implemented in clinical trials in muscle relaxation [22, 27], depth of anesthesia [34, 35], and pain control in patient controlled analgesia [30]. However, most of these applications are dealing with two inputs and one output. When we meet the multivariable self-organizing fuzzy logic structure, it was found that there are still some problems with the SOFLC algorithm after many applications in multivariable structure, mostly in its difficulty to handle the performance index and rule-base in multidimensional space. An idea stimulated by the decomposition of multivariable control rules of fuzzy system into a set of one-dimensional systems led Gupta et al. [9] to a solution of multivariable fuzzy systems. A concept called the decomposition of multivariable self-organizing fuzzy logic structure is presented in this chapter. In Section 14.2 the generic multivariable self-organizing fuzzy logic structures are presented and some formal properties of the structures are discussed. Simulation of anesthesia system either in two-input / two-output or four-input / two-output for SOFLC structures are demonstrated in Section 14.3. Finally, the concluding remarks are given in Section 14.5.

14.2 Multivariable Self-Organizing Fuzzy Logic Structure

Recently research on the application of fuzzy set theory to the design of biomedical control systems has led to interest in the theory and description of the multivariable structure of these systems due to two vital factors. One is real biomedical control systems are multidimensional, and another is the computer implementation of these biomedical systems requires the processing of a huge data base due to the complexity of human being. Therefore, the analysis and design procedures for such systems are consequently very difficult. In search of previous study of SOFLC structure, most of these applications are dealing with two inputs and one output as shown in Figure 14.1.

As an explanatory example, take as the starting point a simple two-input / one-output self-organizing fuzzy logic structure illustrated in Figure 14.2. SOFLC is an extension of a simple fuzzy logic controller with the self-organizing

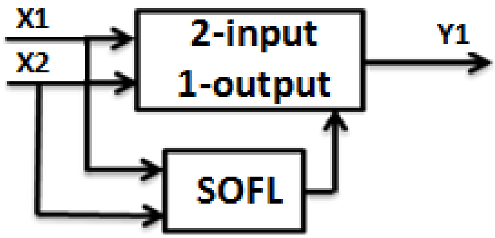


Fig. 14.1. Self-organizing fuzzy logic structure for 2-input / 1-output

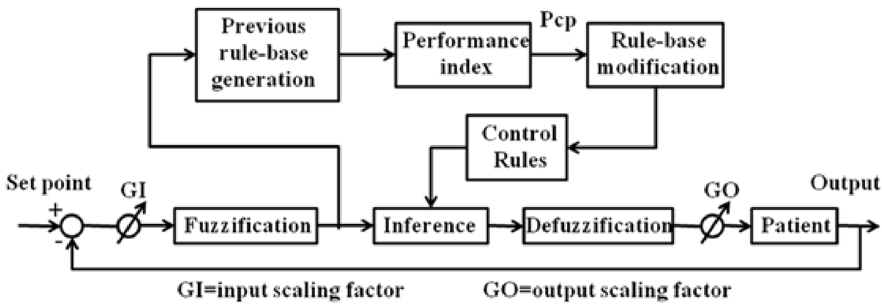


Fig. 14.2. Design of drug controller using a SOFLC algorithm

level that incorporates four new functional blocks: (1) the previous rule-base generation, (2) the performance index, (3) the rule-base modification algorithm, and (4) the control rule-base performance measure.

14.2.1 The Previous Rule-Base Generation

This rule-base can be generated either from expert experience (i.e., medical doctors) or from learning input and output data. Hence, the previous rule-base may have some rules to start with if it begins from expert experience, or may have no rules initially if it starts from zero knowledge. However, after introducing several data into the process, the previous rule-base will be modified by current input and output data. In this chapter, the initial rule-base is generated from simple FLC based on the try-and-error method from our researcher which was expert in fuzzy logic control but only had a little knowledge of anesthesia system.

14.2.2 The Performance Index

The performance index measures the deviation from the desired response and calculates the appropriate changes that are required in the output of the controller. The generation and modification of the control rules is achieved by assigning a credit or reward value to the individual control actions that make a major contribution to the present performance. The credit value is obtained from a fuzzy algorithm which defines the desired performance linguistically and has the

Error	Change in error						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	NS
NS	NB	NB	NS	NS	ZE	PS	PM
ZE	NB	NM	ZE	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PB	PB
PM	NS	ZE	PS	PM	PM	PB	PB
PB	ZE	PS	PM	PM	PB	PB	PB

PB: positive big
PM: positive medium
PS: positive small
ZE: zero
NS: negative small
NM: negative medium
NB: negative big

Fig. 14.3. SOFLC performance index matrix [15]

same form as the control algorithm of the generic fuzzy logic controller. Hence, these linguistic performance rules are derived from a qualitative "feel" for the process and are intended to provide fast convergence around the equilibrium state to achieve high accuracy. For this reason, it is not specific to the type of process being controlled. In other words, this performance index may be very similar for different processes. In this work the performance index was derived from previous research work [15] as shown in Figure 14.3.

14.2.3 The Rule-Base Modification Algorithm

The rule modification procedure can be explained assuming that a process has a time-lag of m samples. If the present instant is nT, this means that the control action at sample (nT-mT) has contributed most to the process performance at the sampling instance nT. Thus, the original implication:

$$E(nT - mT) \rightarrow CE(nT - mT) \rightarrow U(nT - mT)$$

should be changed to:

$$E(nT - mT) \rightarrow CE(nT - mT) \rightarrow U(nT - mT) + P_o(nT)$$

where E and CE are error and change-in-error from the set-point respectively; U is the controller output; P_{cp} is the correction issued by the performance index.

After the rule modification procedure has taken place, a new rule is generated from the input and output data of the controller at each sampling step. The method of logic examination [38] can be employed to obtain the new rules. If the new generated rule has no match in the rule-base, it will be added to rule-base. However, if it already exists in the rule-base, it will be replaced.

14.2.4 The Control Rule-Base Performance Measure

After modifying the three functional blocks, the control rule-base becomes accurate (i.e. no noise contamination and conflicting rules). If the performance of the controller is satisfied by the necessary criteria which are strongly dependent on individual system requirement, the rule-base of the controller will stop modification and the rule-base will converge to a constant rule-base.

However, the multivariable self-organizing fuzzy logic structure as shown in Figure 14.4, still have some problems with the structure when applied to multivariable systems, mostly in its difficulty to handle the performance index and rule-base in multidimensional space. An idea stimulated by the decomposition of multivariable control rules of fuzzy system into a set of one-dimensional systems led Gupta et al. [9] to a solution of multivariable fuzzy systems. A concept called the decomposition of multivariable self-organizing fuzzy logic structure is shown in Figure 14.5 as a simple example for this 3-input and 1-output SOFLC. Furthermore, it is easy to extend this concept to decompose 2-input / 2-output and 3-input / 2-output SOFLC structure in Figure 14.6.

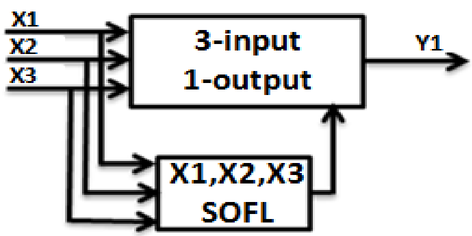


Fig. 14.4. Conventional self-organizing fuzzy logic structure for 3-input / 1-output

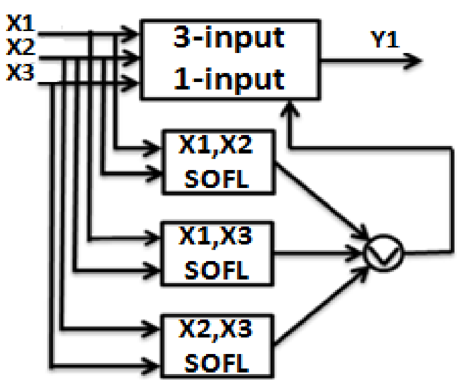
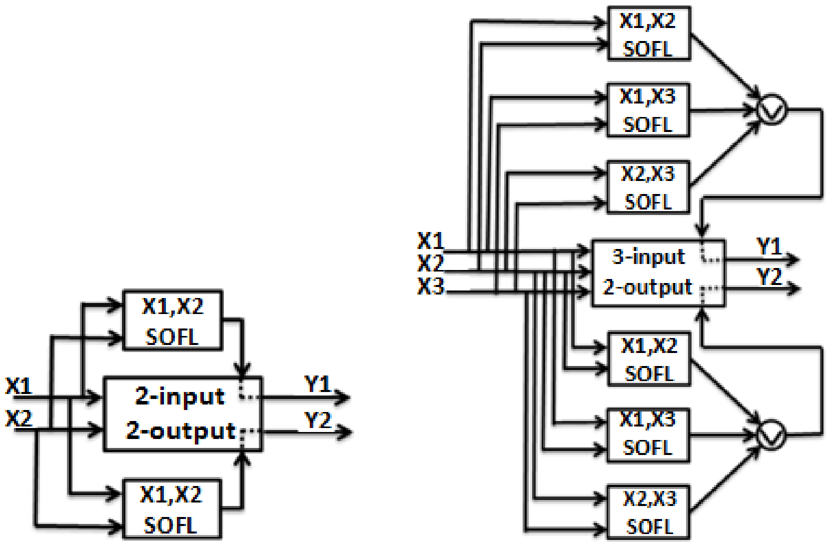


Fig. 14.5. Decomposition of self-organizing fuzzy logic structure for 3-input / 1-output



(a) (b)

Fig. 14.6. Decomposition of self-organizing fuzzy logic structure for 2-input / 2-output and 3-input / 2-output

14.3 Simulation of Anesthesia for Multivariable SOFLC Structures

14.3.1 Simulation Methods

Anesthesia is the art or science of removing sensation of, and reaction to, a surgical procedure. Anesthesia means loss of all sensation whether it is a sense of pain, touch, temperature or position [1]. Modern general anesthesia comprises the triad of muscle relaxation, unconsciousness, and analgesia (i.e. pain relief). Each of these conditions has been considered in recent years as possible scenarios for automated drug infusion via feedback strategies. The major roles performed by a clinical anesthetist are the maintenance of drug-induced muscle relaxation, unconsciousness and analgesia. During the last two decade, the application of simple control (i.e., PID) and advanced control (e.g., adaptive & intelligent) techniques to drug-induced muscle relaxation and unconsciousness in operating theatre has been investigated [3, 13, 16, 20, 21, 31, 32, 34, 35, 36, 39]. The main problem in drug-induced unconsciousness is to measure clinical signs which can be used on-line to the system. The measurement of muscle relaxation is considerably easier via evoked electromyogram (EMG) responses using commercial instruments such as a Datex Relaxograph. Hence, these EMG responses are still as the most general reliable guide for administering intravenous (e.g., atracurium, cisatracurium, or rocurocium) of muscle relaxation control.

However, depth of anesthesia (i.e. unconsciousness) is much harder to define and not readily measurable. In practice, anesthetists have a number of clinical signs and on-line measurements which can be used selectively for the determination of the patient's state. Therefore, many methods have been used for feedback control of anesthetic depth based on different clinical measurements, such as blood pressure [23, 29, 40], electroencephalograph (EEG) signals [33], minimum alveolar concentration (MAC) values [37], plasma concentration of propofol [28] and auditory evoked response (AER) [6, 7]. However, anesthetists still use blood pressure as the most general reliable guide for administering intravenous (e.g., propofol) or inhalational anesthetics (e.g., isoflurane, desflurane, or sevoflurane). The measurement of pain is the hardest of all, since it is heavily subjective, and liable to many levels of personal interpretation. Generally speaking, analgesia is mainly concerned with postoperative conditions. It will not be considered in the simulation of this chapter.

It is considered that the major roles performed by a clinical anesthetist are the maintenance of drug-induced muscle relaxation, unconsciousness, and analgesia. Anesthetic drugs with a rapid onset and short duration of action are highly desirable. The more anesthetists understand the drug's features accurately, the more patient's safety was protected. Pharmacology, the basic for using closed-loop control, consists of two main categories known as pharmacokinetics (PK) and pharmacodynamics (PD). Pharmacokinetics is the study of the concentration of drugs in tissue as a function of time and dose schedule, where as pharmacodynamics is the study of the relationship between drug concentration and effect. Therefore, not only can the anesthetist improve their anesthetic skills through many clinical trials but also by means of pharmacology. In this section of simulation, we use the most common drugs in modern surgery of atracurium for controlling muscle relaxation and isoflurane for controlling blood pressure via their PK-PD compartment models as shown in Figure 14.7 [4].

14.3.2 The Atracurium Mathematical Model

Pharmacokinetics

According to previous studies [17, 18], the drug pharmacokinetics can be expressed by the following equation:

$$G_1(s) = \frac{9.94(1 + 10.64s)}{(1 + 3.08s)(1 + 34.42s)} \tag{14.1}$$

Equation (14.1) describes the pharmacokinetics of the muscle relaxation system relating to the drug atracurium.

Pharmacodynamics

Similarly, to characterize different aspects of drug effect a hypothetical effect compartment is introduced in the above structure (Figure 14.7) leading to the following transfer function:

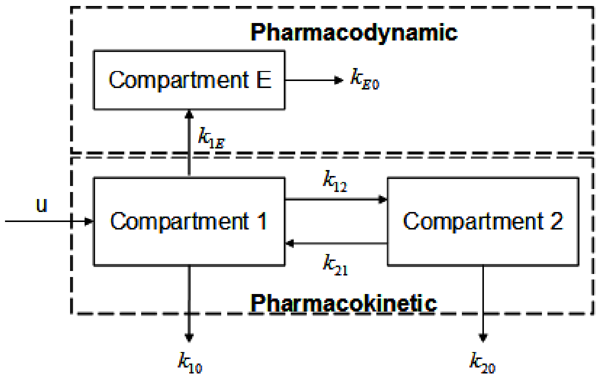


Fig. 14.7. Traditional pharmacological patient model, 2-compartment for pharmacokinetic model and one compartment model for pharmacodynamics, u is system input. The parameters of k_{10} and k_{20} are elimination paths based on Hofmann elimination criteria, k_{12} and k_{21} are first-order rate constants associated with the movement of drug from compartment 1 to compartment 2 and compartment 2 to compartment 1, respectively, and k_{E0} is the rate constant for elimination from the effect compartment.

$$G_{11}(s) = \frac{K_1(1+T_4 s)e^{-\tau_1 s}}{(1+T_1 s)(1+T_2 s)(1+T_3 s)} \tag{14.2}$$

where τ_1= 1 min, K_1 = 1, T_1= 4.81 min, T_2= 34.42 min, T_3= 3.08 min, T_4= 10.64 min. Moreover, the following non-linearity represented by a Hill equation is used to relate the effect to a specific drug concentration:

$$E_{eff} = E_{\max} \frac{X_E^{\alpha}}{X_E^{\alpha} + (X_E(50))^{\alpha}} \tag{14.3}$$

where X_E is the drug concentration, α the power and $X_E(50)$ the drug concentration at 50% effect with the following values**:** E_{max} = 100%, $X_E(50)$ = 0.404 $\mu g\ ml^{-1}$, $\alpha = 2.98$.

14.3.3 The Isoflurane Unconsciousness Model

There is no doubt that anything that is related to the human brain represents a very complex entity, and anesthesia or unconsciousness which affects the brain has indeed been the subject of many conflicting views. Hence, depth of anesthesia (i.e. unconsciousness) is much harder to define and not readily measurable. In practice, anesthetists have a number of clinical signs and on-line measurements which can be used selectively for the determination of the patient's state. Routinely, anesthetists still use blood pressure as the most general reliable guide for inhalational anesthetics (e.g., isoflurane, desflurane, or sevoflurane) or administering intravenous (e.g., propofol). Hence, in studies conducted by previous groups [24], step responses to changes in inspired concentration of isoflurane from a vaporizer were performed. If the changes in inhaled isoflurane concentration are small (i.e., less than 5 %), the responses could be approximated by linear characteristics. However, if the changes do not fall within this range, the responses are in general non-linear and time-varying. Thus, a first-order linear model with dead-time has been adopted, having a time-constant of 1-2 minutes. The magnitude of the time-constant is long enough to absorb some inaccuracy of dead-time estimate due to breathing variation. On the other hand, in order to estimate the steady-state gain, it is assumed that a relatively sensitive patient needs 2 % isoflurane for a 30 mmHg reduction in MAP. Therefore, the model describing variations of blood pressure to small changes in inhaled isoflurane concentration can be written as:

$$G_{22}(s) = \frac{\Delta MAP(s)}{U_2(s)} = \frac{K_2 e^{-\tau_2 s}}{(1 + T_5 s)} \tag{14.4}$$

where τ_2= 0.42 min, T_5= 2 min, K_2= -15 mmHg/percent.

14.3.4 Interactive Component Model

Regarding atracurium to blood pressure interaction [18], this has been investigated in human beings and there seems to be a small increase in heart rate when atracurium is administered. As an initial approximation, therefore, this pathway has been ignored in the dynamic model. However, it should be noted that this may not be approximate for other drugs for unconsciousness, such as other inhalational drugs, such as desflurane or sevoflurane. On the other side, the interaction of isoflurane to muscle relaxation is small but significant. An experiment was performed by Dr Asbury in 1990, in which a patient of 47 without a kidney but having a renal transplant was anaesthetized. Step changes of $0 \sim 1$ % isoflurane infusions were superimposed on steady relaxation levels achieved 50 minutes into the operation via atracurium infusion. Transient responses for both on and off conditions were obtained, and dynamics estimated for each case. Because there was not a large difference between the phases, an averaged transfer function was obtained as follows:

$$G_{12}(s) = \frac{K_4 e^{-\tau_4 s}}{(1 + T_6 s)(1 + T_7 s)} \tag{14.5}$$

where τ_4= 1 min, T_6= 2.83 min, T_7= 1.25 min, K_4= 0.27 .

14.3.5 The Overall Multivariable Anesthetic Model

From the previous sections description, the overall linear multivariable system combining muscle relaxation (i.e., paralysis) together with unconsciousness (in terms of blood pressure measurements) can be summarized by the following system:

$$\begin{bmatrix} Paralysis \\ \Delta MAP \end{bmatrix} = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ 0 & G_{22}(s) \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} \tag{14.6}$$

where

$$G_{11}(s) = \frac{1.0e^{-s}(1 + 10.64s)}{(1 + 3.08s)(1 + 4.81s)(1 + 34.42s)}$$

$$G_{12}(s) = \frac{0.27e^{-s}}{(1 + 2.83s)(1 + 1.25s)}$$

$$G_{22}(s) = \frac{-15.0e^{-0.42s}}{(1 + 2s)}$$

Finally, the overall non-linear multivariable system combining all the effects is obtained by including the non-linearity of pharmacodynamics of atracurium drug only since isoflurane drug-effect is considered to reflect linear characteristics within a range already specified in the preceding sections.

14.4 Simulation Results

In order to demonstrate the performance of the proposed multivariable SOFLC structure, the model has been taken the equation (14.6) for simulation this two-input (i.e., muscle relaxation error and blood pressure error), and two-output (i.e., atracurium and isoflurane), anesthesia control system using fuzzy logic and self-organizing fuzzy logic structures. Moreover, in order to reduce the steady-state errors, the error integrations of muscle relaxation and blood pressure have been considered for simulation this four-input (i.e., muscle relaxation error, muscle relaxation integration error, blood pressure error, and blood pressure integration error), and two-output (i.e., atracurium and isoflurane), anesthesia control system using fuzzy logic and self-organizing fuzzy logic structures as well. Hence, four kinds of fuzzy logic structures have been considered in this work, as described in the following.

14.4.1 Fuzzy Logic Control of Two-Input and Two-Output Anesthesia System

Figure 14.8 shows the FLC closed-loop control structure of the two-input and two-output anesthesia system. Control rules, membership functions, fuzzy inference engine and defuzzification are the essential elements in the fuzzy logic control. To perform fuzzy inference and describe this FLC control system, we chose two inputs which were the error of muscle relaxation (i.e., M_e) and the error of blood pressure (i.e., B_e) and two outputs which were the atracurium infusion rate (i.e., Atra_Inf) and isoflurane concentration (i.e., Iso_Conc). So, the fuzzy logic structure for this two-input and two-output is shown in Figure 14.9.

In order to fuzzify the inputs and output, the error of muscle relaxation (M_e) and the error of blood pressure (B_e) were divided into seven levels, namely negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), and positive big (PB). The change of atracuriun infusion (Atra_Inf) and isoflurane concentration (Iso_Conc) were divided into four levels, namely zero (ZE), positive small (PS), positive

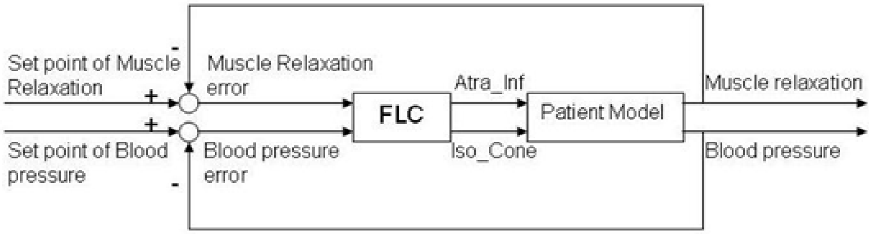


Fig. 14.8. Closed loop FLC system

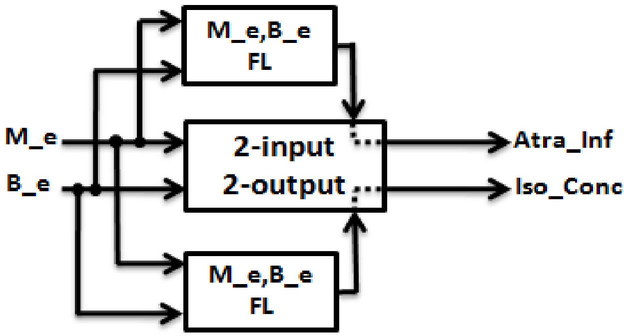


Fig. 14.9. The fuzzy logic structure for this two-input / two-output

Atra_Inf	NB	NM	NS	ZE	PS	PM	PB
NB	PB		PS		ZE		ZE
NM		PM		ZE		ZE	
NS	PB		PS		ZE		ZE
ZE		PM		ZE		ZE	
PS	PM		ZE		ZE		ZE
PM		PM		ZE		ZE	
PB	PM		ZE		ZE		ZE

(a)

Iso_Conc	NB	NM	NS	ZE	PS	PM	PB
NB	ZE		ZE		ZE		ZE
NM		ZE		ZE		ZE	
NS	ZE		ZE		ZE		ZE
ZE		ZE		ZE		ZE	
PS	PS		PS		PS		ZE
PM		PM		PS		ZE	
PB	PB		PM		PS		PS

(b)

Fig. 14.10. The rule-bases of two-input and two-output for fuzzy logic (a) Atracurium rule-base (b) Isoflurane rule-base

medium (PM), and positive big (PB). There is no negative fuzzy set because the absolute output values of atracurium infusion and isoflurane concentration were used in this simulation so there are no negative values of these infusion rate and concentration. There are many shapes of possible membership functions, such as triangle and trapezoid, which can be used in the fuzzy logic controller. In this study, a triangular shape is used and a 25% overlap for contiguous fuzzy sets is reckoned [12] for two inputs (M_e and B_e), and two outputs (Atra_Inf and Iso_Conc). A try-and-error method was adopted to generate the initial rule-base; this method is based on good knowledge of fuzzy logic but less in anesthesia. Twenty five rules were developed to control the system as shown in Figure 14.10. In this simulation, the set points of muscle relaxation and blood pressure were set to 80% paralysis and 110 mmHg respectively. Each simulation was performed for 150 min surgical operation. The simulation results are shown in Figure 14.11. Unfortunately, these initial rules gave poor control of the muscle relaxation and blood pressure where some steady state errors occurred. Therefore the rule-bases need to be modified due to the poor designed rule which were generated by a non expert in anesthesia. Hence, this could be done using a SOFLC algorithm to further fine-tune the rule-bases.

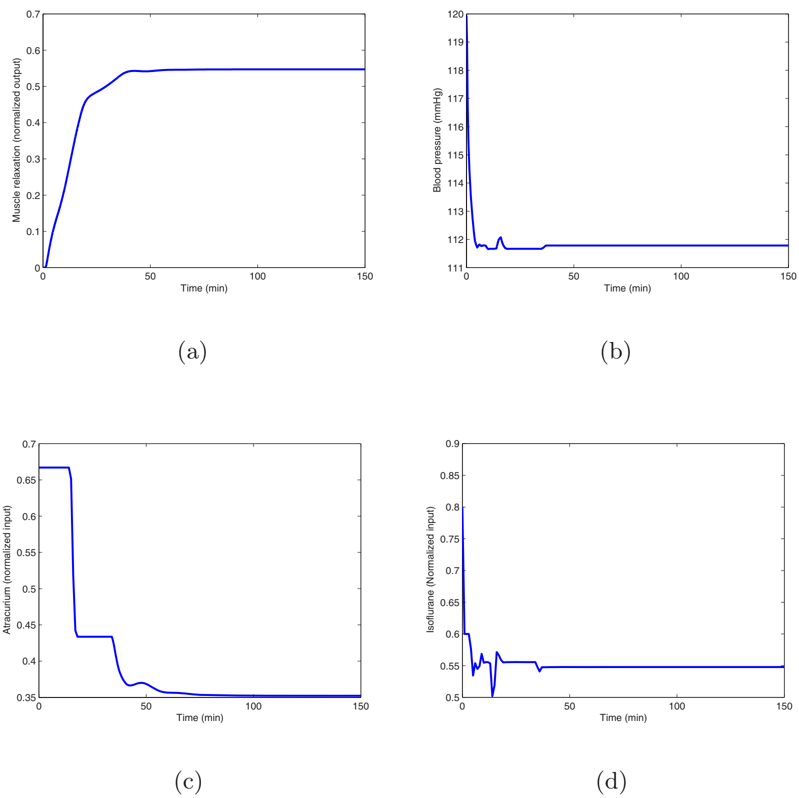


Fig. 14.11. The simulation of two-input and two-output anesthesia system using fuzzy logic (a) Muscle relaxation output (b) Blood pressure output (c) Atracurium input (d) Isoflurane input

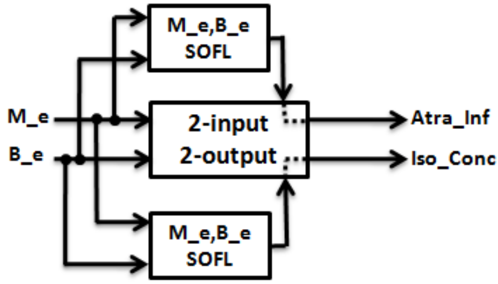


Fig. 14.12. The two-input and two-output anesthesia system using SOFLC structure

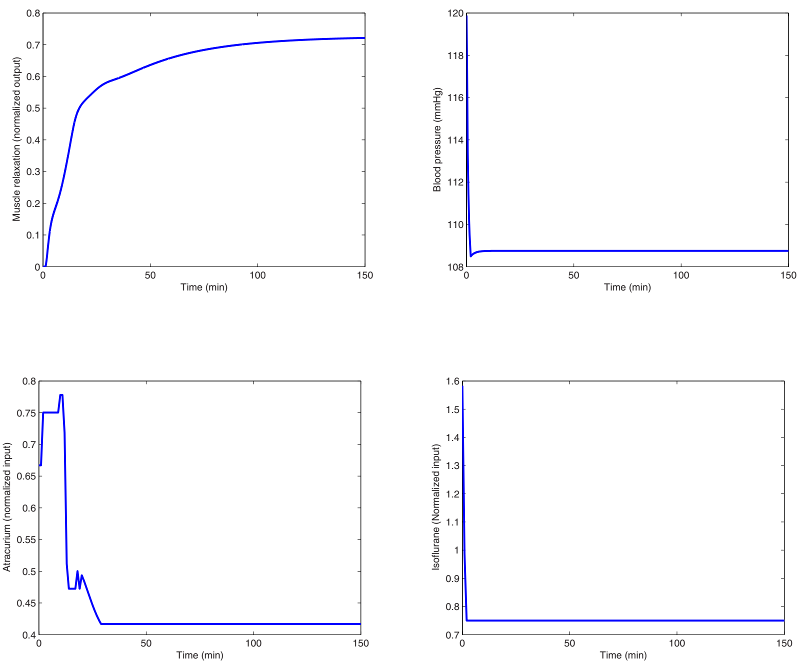


Fig. 14.13. The simulation of two-input and two-output anesthesia system using SOFLC (a) Muscle relaxation output (b) Blood pressure output (c) Atracurium input (d) Isoflurane input

14.4.2 Self-Organizing Fuzzy Logic Control of Two-Input and Two-Output Anesthesia System

SOFLC is a two-level hierarchical controller. The basic level is a simple fuzzy logic controller, while the second level is a self-organizing level that supervises the basic level by monitoring its performance, subsequently generating and modifying the control rules. Hence, we applied this SOFLC in multivariable structure of two-input and two-output anesthesia simulation system. The SOFLC

Atra_Inf	NB	NM	NS	ZE	PS	PM	PB
NB	PB		PS		ZE		ZE
NM		PM		ZE		ZE	
NS	PB		PS		ZE		ZE
ZE	*PB*	*PB*	*PM*	*PM*		ZE	
PS	PM		ZE		ZE		ZE
PM	*PB*	PM		ZE		ZE	
PB	PM		ZE		ZE		ZE

(a)

Iso_Conc	NB	NM	NS	ZE	PS	PM	PB
NB	ZE		ZE		ZE		ZE
NM		ZE		ZE		ZE	
NS	ZE		ZE		ZE		ZE
ZE	*PS*	*PS*	*PS*	*PS*		ZE	
PS	*PM*		PS		PS		ZE
PM	*PM*	PM		PS		ZE	
PB	PB		PM		PS		PS

(b)

Fig. 14.14. The rule-bases of two-input / two-output for SOFLC (a) Atracurium rule-base (b) Isoflurane rule-base (Notation: The italic and underline rules in the atracurium and isoflurane rule-bases represented generated from self-organized fuzzy logic algorithm)

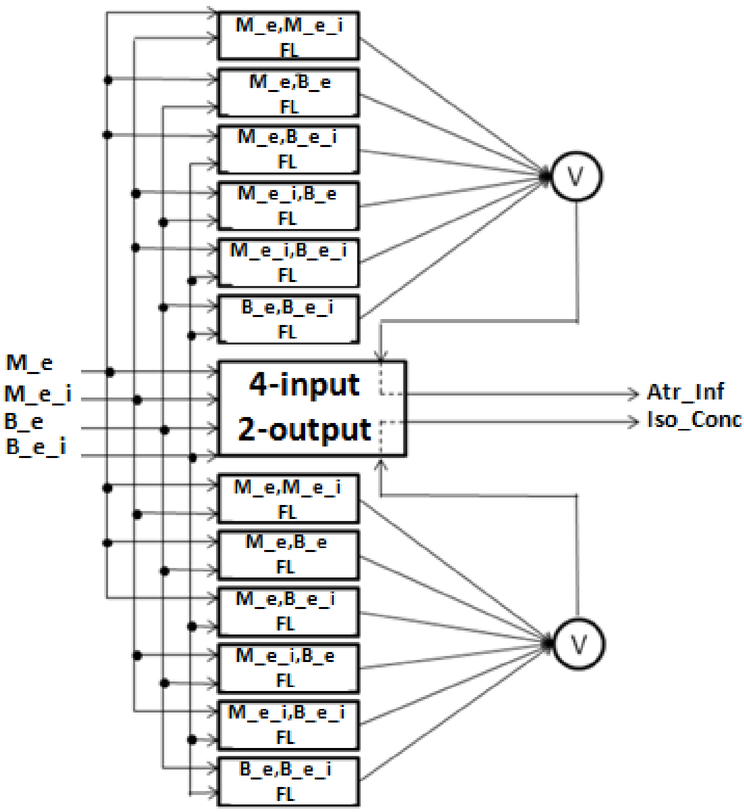


Fig. 14.15. The fuzzy logic structure for this four-input / two-output

Atra_Inf	NB	NM	NS	ZE	PS	PM	PB
NB	ZE PB / PB PB / PB PB		ZE PM / PS PS / PM PS		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE
NM		ZE PM / PM PM / PM PM		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE	
NS	ZE PM / PB PB / PB PB		ZE PS / PS PS / PS PS		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE
ZE		ZE PM / PM PM / PM PM		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE	
PS	ZE PS / PM PM / PB PB		ZE PS / ZE ZE / PS PS		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE
PM		ZE PS / PM PM / PS PM		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE	
PB	ZE PS / PM PM / PB PB		ZE PS / ZE ZE / PS PS		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE

Iso_Conc	NB	NM	NS	ZE	PS	PM	PB
NB	ZE PB / ZE ZE / ZE ZE		ZE PM / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE		PS ZE / ZE ZE / ZE ZE
NM		ZE PM / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE		PS ZE / ZE ZE / ZE ZE	
NS	ZE PS / ZE ZE / ZE ZE		ZE PS / ZE ZE / ZE ZE		PS ZE / ZE ZE / ZE ZE		PM ZE / ZE ZE / ZE ZE
ZE		ZE ZE / ZE ZE / ZE ZE		ZE ZE / ZE ZE / ZE ZE		PM ZE / ZE ZE / ZE ZE	
PS	ZE ZE / PS PS / PS PM		PS ZE / PS PS / PS PS		PS ZE / PS PS / PS ZE		PB ZE / ZE ZE / ZE ZE
PM		PS ZE / PM PM / PM PM		PM ZE / PS PS / PS PS		PB ZE / ZE ZE / ZE PS	
PB	PS ZE / PB PB / PB PB		PM ZE / PM PM / PM PM		PB ZE / PS PS / PS PS		PB ZE / PS PS / PS PS

Fig. 14.16. The rule-bases of four-input / two-output for fuzzy logic (a) Atracurium rule-base (b) Isoflurane rule-base

structure was shown in Figure 14.12. In order to compare it to a basic fuzzy logic controller, the set points and partition of fuzzy sets for the inputs and outputs were the same used in the previous method. Also, in this simulation,

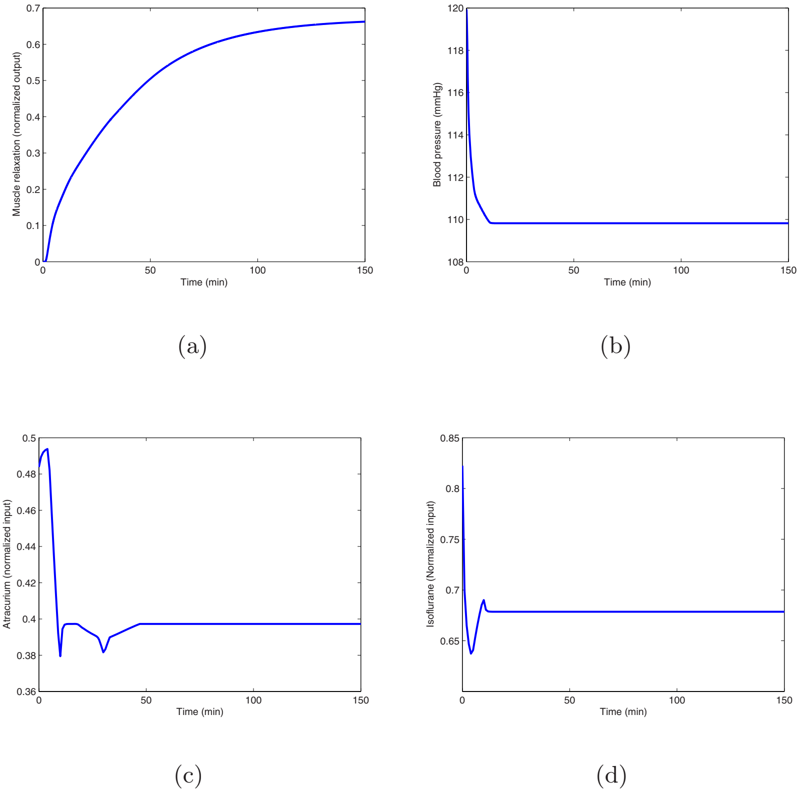


Fig. 14.17. The simulation of two-input and two-output anesthesia system using fuzzy logic (a) Muscle relaxation output (b) Blood pressure output (c) Atracurium input (d) Isoflurane input

the initial rule-base (i.e., 25 rules) was taken from the previous basic FLC. The simulation results are shown in the Figure 14.13. The controller performance is better than the previous method but the steady state error still dominant in the outputs although some rules were generated by self-organizing fuzzy logic structure as shown in Figure 14.14. Therefore, the control structure needs to be modified in order to overcome the steady state error problems.

14.4.3 Fuzzy Logic Control of Four-Input/Two-Output Anesthesia System

In order to reduce the steady state error, an integration of the error was considered as an input to the system. Hence, four inputs were defined as the error of muscle relaxation (M_e), the integration error of muscle relaxation (M_e_i), the error of blood pressure (B_e), and the integration error of blood pressure (B_e_i). Whereas the two outputs were the same as in the previous method, namely atracurium

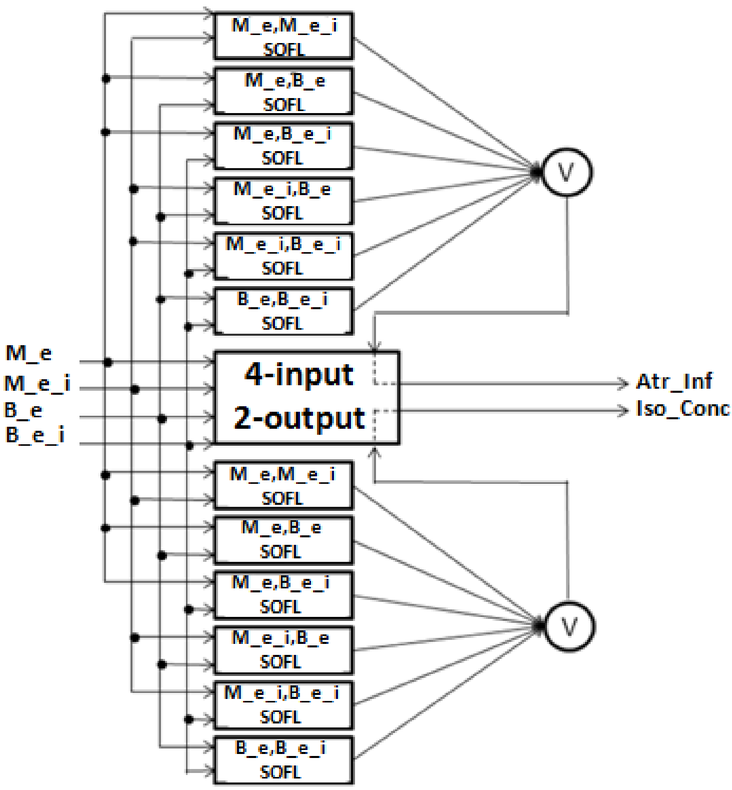


Fig. 14.18. The SOFLC structure for four-input / two-output structure

Table 14.1. The steady state errors of muscle relaxation and blood pressure of these four methods

	FLC (2-input / 2-output)	SOFLC (2-input / 2-output)	FLC (4-input / 2-output)	SOFLC (4-input / 2-output)
Muscle Relaxation Steady-state error	-0.25293	-0.078626	-0.13776	-0.006190
Blood Pressure Steady-state error	1.7836	-1.25	-0.17889	0.065204

infusion rate (Atra_Inf) and isoflurane concentration (Iso_Conc). The controller structure (four-input / two-output) is shown in Figure 14.15. According to try-and-error method, the designer (expert in fuzzy logic control but only had a little

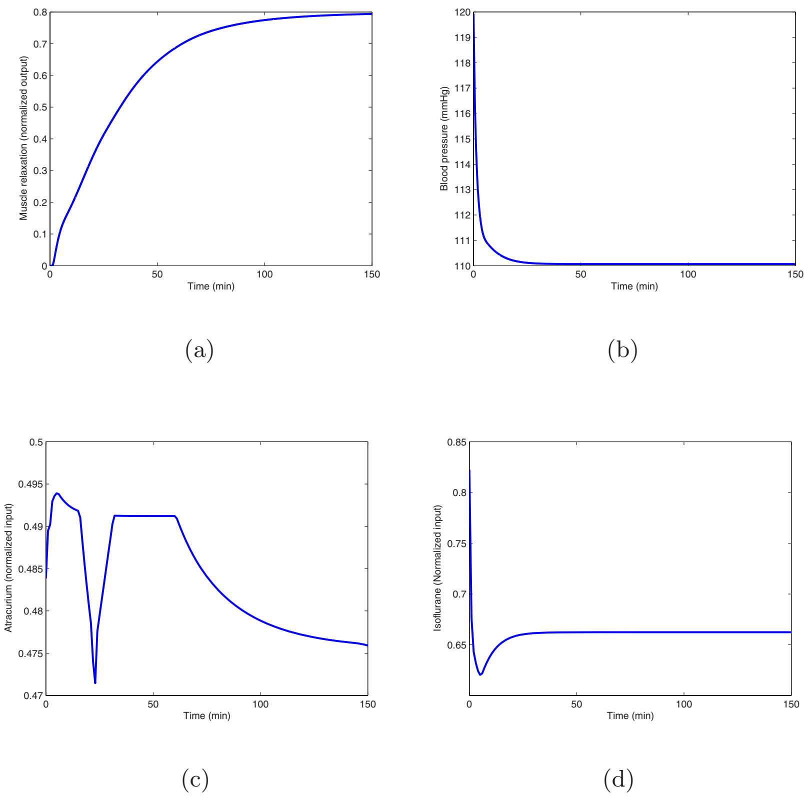
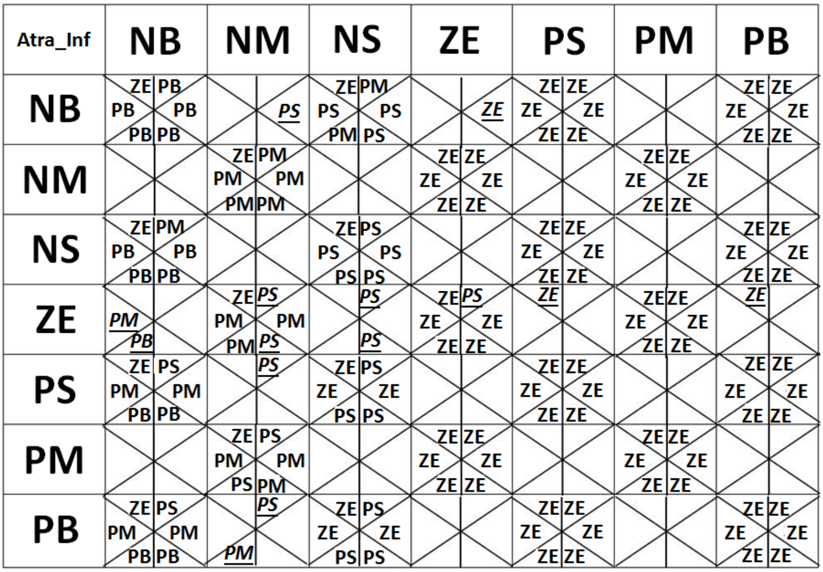


Fig. 14.19. The simulation of four-input / two-output anesthesia system using SOFLC (a) Muscle relaxation output (b) Blood pressure output (c) Atracurium input (d) Isoflurane input

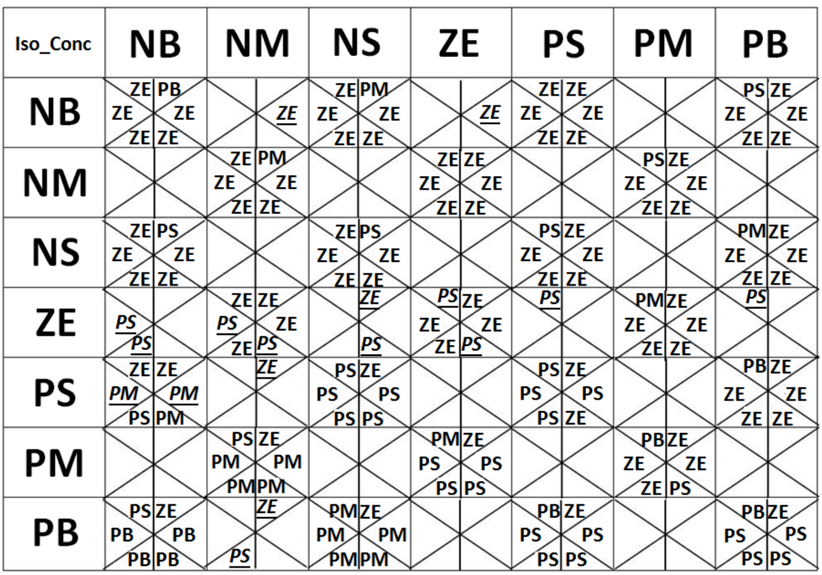
knowledge of anesthesia system) has generated both rule-bases for controlling the atracurium infusion and isoflurane concentration. Six fuzzy rule-bases were developed; each has twenty five rules as shown in Figure 14.16. In order to compare with the two-input / two-output structure, the set points and partition of the fuzzy sets for the inputs and outputs were the same used in the previous method. The simulation results are shown in the Figure 14.17. The steady state error of blood pressure was reduced dramatically but the steady state error of muscle relaxation still exists. Hence, the SOFLC algorithm can be utilized to further fine-tune the rule-bases for each case according to previous experience.

14.4.4 Self-Organizing Fuzzy Logic Control of Four-Input/Two-Output Anesthesia System

The SOFLC system was applied to multivariable structure of four-input / two-output anesthesia simulation system as shown in Figure 14.18. In order to



(a)



(b)

Fig. 14.20. The rule-bases of four-input and two-output for SOFLC (a) Atracurium rule-base (b) Isoflurane rule-base (Notation: The italic and underline rules in the atracurium and isoflurane rule-bases generated by SOFLC)

compare with the basic fuzzy logic controller, the set points and partition of fuzzy sets of the inputs and outputs were the same used in the previous method. Also, in this simulation, the initial rule-base (i.e., 25 rules) that is generated for the simple FLC was used. The simulation results are shown in the Figure 14.19. The steady state error of muscle relaxation was reduced dramatically and the steady state error of blood pressure is better controlled due to the addition of new rules which were generated by self-organizing fuzzy logic structure as shown in Figure 14.20.

Finally, the steady state errors of these four methods were are tabulated in Table 14.1. It is shown that the steady state error of the SOFLC with four-input / two-output structure is the smallest in terms of muscle relaxation and blood pressure compared to that of the other three multivariable structures.

14.5 Conclusions

In this chapter, we have demonstrated that a multivariable SOFLC can provide more stable muscle relaxation and blood pressure by administering atracurium infusion rate and isoflurane concentration when rule-base modifications have been considered in comparison with a simple fuzzy logic which has fixed rule-bases. Two important aspects have been addressed in this chapter for simulating anesthesia control in the operating theatre. First, using decomposition of multivariable self-organizing fuzzy logic structure, we are able to handle the performance index and rule-base in multidimensional space. Second, the SOFLC algorithm has a learning ability which is similar to the way in which human experts use experiential knowledge or no knowledge to learn a clinical rule-base protocol for anesthesia control (i.e., learning-by-example). In this chapter, several new rules, which are not in the initial rule-base, were generated by the self-organizing learning process via 150 min simulation. Moreover, the simulations explored how the multivariable SOFLC algorithm compensates for the missing knowledge from the initial rule-bases, this evidence provides an insight view on how rules migrate and converge.

However, this study demonstrates the feasibility and applicability of the multivariable SOFLC in anesthesia control. But, it still needs a series of clinical trials at operating theatre, perhaps to refine the multivariable SOFLC, and certainly to show how widely they can be applied. Therefore, this presentation is by no means complete and it aims to give an idea of whether multivariable SOFLC can mimic human being thinking for monitoring multiple sensors and administering multiple drugs in the operating theatre. Also it can show whether the decomposition of multivariable self-organizing fuzzy logic structure can provide better performance when the rule-bases are modified. In this sense, an initial rule-base (i.e., 25 rules) is from simple decomposed fuzzy logic controllers that construct a 2-input / 2-output or 4-input / 2-output structure. The SOFLC features will modify the decomposed rule-bases separately to give the multivariable algorithm strength in combating complex systems. The current research can now be expanded to encompass alternative intravenous techniques and different intravenous drugs (e.g., propofol, midazolam, morphine). In addition, the multivariable SOFLC could be expanded to include other closed-loop control in analgesia or NICU, such as multivariable pain control in extra corporeal shock wave lithotripsy [30] and even more complex multivariable control problems, such as the treatment of cerebral perfusion for controlling MAP and ICP in NICU [10].

Currently, fuzzy logic, neural networks and genetic algorithms are three popular artificial intelligence techniques that are widely used in many applications. Due to their distinct properties and advantages, they are currently being investigated and integrated to form models or strategies in the areas of system control. In control engineering, the fusion of fuzzy logic, neural networks and genetic algorithms is steadily growing [2, 33]. Therefore, using the hybrid intelligent approach to auto-tuning the parameters of the fuzzy logic controller may provide more suitable clinical control of anesthesia in operating theatre. However, the characteristics of on-line self-learning have lead the SOFLC to be more suitable for real time control in comparison with off-line analysis of the neural networks and genetic algorithms which are more time consuming.

References

1. Adams, A.P., Cashman, J.N.: Anaesthesia, analgesia and intensive care. Edward Arnold, London (1991)
2. Allen, R., Smith, D.: Neuro-fuzzy closed-loop control of depth of anaesthesia. Artificial Intelligence in Medicine 21, 185–191 (2001)
3. Chuang, C.T., Fan, S.Z., Shieh, J.S.: Muscle relaxation controlled by automated administration of cisatracurium. Biomedical Engineering- Applications, Basis & Communications 18(6), 284–295 (2006)
4. Chuang, C.T., Fan, S.Z., Shieh, J.S.: The use of intensive manual control to model cisatracurium pharmacokinetics and pharmacodynamics for neuromuscular block. Journal of Medical and Biological Engineering 26(4), 187–193 (2006)
5. Ciresi, G., Akay, M.: Fuzzy logic in medical control applications. Biomedical Engineering-Applications Basis Communications 8(6), 471–487 (1996)
6. Elkfafi, M., Shieh, J.S., Linkens, D.A., Peacock, J.E.: Intelligent signal processing of evoked potentials for anaesthesia monitoring and control. IEE Proc. Control Theory and Appl. 144(4), 354–360 (1997)
7. Elkfafi, M., Shieh, J.S., Linkens, D.A., Peacock, J.E.: Fuzzy logic for auditory evoked response monitoring and control of depth of anaesthesia. Fuzzy Sets and Systems 100, 29–43 (1998)
8. Gao, Y., Er, M.J.: Online adaptive fuzzy neural identification and control of a class of mimo nonlinear systems. IEEE Transactions on Fuzzy Systems 11(4), 462–477 (2003)
9. Gupta, M.M., Kiszka, J.B., Trojan, G.M.: Multivariable structure of fuzzy control systems. IEEE Transactions on Systems, Man, and Cybernetics 16(5), 638–656 (1986)
10. Huang, S.J., Shieh, Fu, M., Kao, M.C.: Fuzzy logic control for intracranial pressure via continuous propofol sedation in a neurosurgical intensive care unit. Medical Engineering & Physics 28(7), 639–647 (2006)

11. Kim, Y.T., Bien, Z.: Robust self-learning fuzzy controller design for a class of nonlinear mimo systems. Fuzzy Sets and Systems 111(2), 117–135 (2000)
12. Kosko, B.: Neural networks and fuzzy systems. Prentice-Hall International, Inc., Singapore (1991)
13. Linkens, D.A.: Adaptive and intelligent control in anesthesia. IEEE Control Systems Magazine, 6–11 (1992)
14. Linkens, D.A.: The role of intelligent systems engineering in biomedicine. Biomedical Engineering - Applications Basis Communications 8(5), 385–391 (1996)
15. Linkens, D.A., Hasnain, S.B.: Self-organizing fuzzy logic control and application to muscle relaxant anaesthesia. IEE Proceedings, Part D 138, 274–284 (1991)
16. MacLeod, A.D., Asbury, A.J., Gray, W.M., Linkens, D.A.: Automatic control of neuromuscular block with atracurium. British Journal of Anaesthesia 63, 31–35 (1989)
17. Mahfouf, M.: Generalised predictive control (gpc) in the operating theatre. In: Linkens, D.A. (ed.) Intelligent Control in Biomedicine, pp. 37–78. Taylor & Francis, London (1994)
18. Mahfouf, M., Abbod, M.F.: A comparative study of generalized predictive control (gpc) and intelligent self-organizing fuzzy logic control (soflc) for multivariable anaesthesia. In: Linkens, D.A. (ed.) Intelligent Control in Biomedicine, pp. 79–132. Taylor & Francis, London (1994)
19. Mahfouf, M., Abbod, M.F., Linkens, D.A.: Survey of fuzzy logic monitoring and control utilization in medicine. Artificial Intelligence in Medicine 21(1), 27–42 (2001)
20. Mahfouf, M., Linkens, D.A., Asbury, A.J., Gray, W.M., Peacock, J.E.: Generalised predictive control (gpc) in the operating theatre. IEE Proceedings, Part D 139, 404–420 (1992)
21. Martin, J.F., Smith, N.T., Quinn, M.L., Schneider, A.M.: Supervisory adaptive control of arterial pressure during cardiac surgery. IEEE Transactions on Biomedical Engineering 39(4), 389–393 (1992)
22. Mason, D.G., Ross, J.J., Edwards, N.D., Linkens, D.A., Reilly, C.S.: Self-learning fuzzy control of atracurium-induced neuromuscular block during surgery. Medical & Biological Engineering & Computing 35, 498–503 (1997)
23. Meier, R., Nieuwland, J., Zbinden, A.M., Hacisalihzade, S.S.: Fuzzy logic control of blood pressure during anesthesia. IEEE Control Systems Magazine 12(12), 12–17 (1992)
24. Millard, R.K., Monk, C.R., Woodcock, T.E., Roberts, C.P.: Controlled hypotension during ent surgery using self-tuners. Computational Biology and Medicine 17, 1–18 (1988)
25. Nie, J., Lee, T.H.: Self-organizing rule-based control of multivariable nonlinear servomechanisms. Fuzzy Sets and Systems 3, 285–304 (1997)
26. Procyk, T.J., Mamdani, E.H.: A linguistic self-organizing process controller. Automatica 15, 15–30 (1979)
27. Ross, J.J., Mason, D.G., Linkens, D.A., Edwards, N.D.: Self-learning fuzzy logic control of neuromuscular block. British Journal of Anesthesia 78, 412–415 (1997)
28. Shieh, J.S., Chang, L.W., Fan, S.Z., Liu, C.C.: Fuzzy logic control of propofol infusion using quantitative and qualitative approaches. Biomedical Engineering-Applications, Basis & Communications 9(6), 350–360 (1997)
29. Shieh, J.S., Chang, L.W., Fan, S.Z., Liu, C.C., Huang, H.H.: Automatic control of anaesthesia using hierarchical structure. Biomedical Engineering-Applications, Basis & Communication 10(4), 195–202 (1998)

30. Shieh, J.S., Chang, L.W., Yang, T.C., Liu, C.C.: An enhanced patient controlled analgesia (epca) for the extracorporeal shock wave lithotripsy (eswl). Biomedical Engineering-Applications, Basis & Communications 19(1), 7–17 (2007)
31. Shieh, J.S., Fan, S.Z., Chang, L.W., Liu, C.C.: Hierarchical rule-based monitoring and fuzzy logic control for neuromuscular block. Journal of Clinical Monitoring and Computing 16, 583–592 (2000)
32. Shieh, J.S., Fan, S.Z., Shi, W.L.: The intelligent architecture for simulation of inhalational anaesthesia. Biomedical Engineering-Application, Basis & Communications 16(5), 272–280 (2004)
33. Shieh, J.S., Kao, M.H., Liu, C.C.: Genetic fuzzy modelling and control of bispectral index (bis) for general intravenous anaesthesia. Medical Engineering & Physics 28(2), 134–148 (2006)
34. Shieh, J.S., Linkens, D.A., Asbury, A.J.: A hierarchical system of on-line advisory for monitoring and controlling the depth of anesthesia using self-organizing fuzzy logic. Engineering Applications of Artificial Intelligence 18(3), 307–316 (2005)
35. Shieh, J.S., Linkens, D.A., Peacock, J.E.: Hierarchical rule-based and self-organizing fuzzy logic control of anesthesia. IEEE Transaction on Systems, Man, and Cybernetics, Part C: Applications and Reviews 9(1), 98–109 (1999)
36. Shieh, J.S., Linkens, D.A., Peacock, J.E.: A computer screen-based simulator for hierarchical fuzzy logic monitoring and control of depth of anaesthesia. Mathematics and Computers in Simulation 67(3), 251–265 (2004)
37. Tatnall, M.L., Morris, P., West, P.G.: Controlled anaesthesia: An approach using patient characteristics identified during uptake. British Journal of Anaesthesia 53, 1019–1026 (1981)
38. Tong, R.M.: Synthesis of fuzzy models for industrial processes – some recent results. International Journal of General Systems 4, 143–162 (1978)
39. Uys, P.C., Morrell, D.F., Bradlow, H.S., Rametti, L.B.: Self-tuning microprocessor-based closed-loop control of atracurium-induced neuromuscular blockade. British Journal of Anaesthesia 61, 685–692 (1988)
40. Zbinden, A.M., Feigenwinter, P., Petersen-Felix, S., Hacisalihzade, S.: Arterial pressure control with isoflurane using fuzzy logic. British Journal of Anaesthesia 74, 66–72 (1995)