Multivariable Fuzzy Logic/Self-organizing for Anesthesia Control

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Abstract

In operating theatres, anesthetists usually adopt a specific regime to administer anesthetic drugs during the different stages of the operation. Hence, designing an automatic closed loop control system cannot be realized with a fixed control system for the consecutive stages of the operation. A multi-stage controller that can change from fixed to adaptive regimes would be an attractive solution. In order to imitate the anesthetist, a linguistic controller can be a feasible solution. Fuzzy logic theory provides such facility with linguistic rule bases defined as the control regime. The controller can be designed with different stages and fixed, self-organizing, incremental and absolute control actions. In this work, a novel method for decomposing an m-input/n-output self-organizing fuzzy logic control (SOFLC) structure to many 2-input/1-output sets has been designed for controlling general anesthesia and muscle relaxation for the operating theatre. Successful simulation results have given us confidence to perform clinical trials in the operating theater in the near future.

Keywords: Multivariable self-organizing fuzzy logic control structure, Self-organizing fuzzy logic control (SOFLC), Fuzzy logic control

1. Introduction

In biomedical control systems, there are many factors that make designing an automatic controller difficult. This is due to the nature of humans: differences from one person to another, dynamic changes in the human response to external stimuli, the effect of the different drugs on patients, and human bodies being highly non-linear and multivariable [1,2]. On the other hand, intelligent control systems, with their counterpart model-based structures, are well suited to control such systems due to their success in dealing with complex multivariate uncertain systems without the need for extensive dynamic modeling. The main difficulty in the multivariable case is the interaction between variables and sensitivity to faults in various channels. At the forefront of intelligent control systems technology are fuzzy logic control (FLC), neural networks (NN) and genetic algorithms (GA), which have all proved to be highly useful for many other existing forms of control.

Fuzzy logic control has a long history. It stems from the theoretical work of Lotfi Zadeh [3,4]. He proposed the use of fuzzy logic to mimic the human’s ability to use imprecise statements to solve complex problems. The main four components of FLC are fuzzification, knowledge base, inference engine, and defuzzification [5]. The fuzzification process converts the measured input into a corresponding linguistic value. The knowledge-base comprises the settings of the controller parameters, such as the labels, fuzzy sets shapes and type and number of rules [6].

An extension to FLC is the self-organizing fuzzy logic control (SOFLC), which has the ability to generate and modify the rule base. This feature makes the controller adaptive to any changes in the controlled system. The controller consists of two levels; the first level is a simple fuzzy controller, while the second level consists of the self-organizing mechanism, which acts as a monitor and an evaluator of the controller performance. In the first level, the input signal to the controller is taken at each sampling instant in the form of error and change-in-error. Each signal is mapped to its correspondent discrete level by using the error and change-in-error scaling factors respectively and sent to the self-organizing controller (SOC). The SOC, according to control rules issued by the second level, calculates the output with respect to the inputs. The output control signals are scaled to real values using the output scaling factors and sent to the process being controlled. The second level consists of four blocks: the performance index, the process reference model, the rules modifier, and the state buffer. Further details on

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the design of a SOFLC can be found elsewhere [7-9] but it suffices here to concentrate on the learning part.

The SOC is based on observation of the trajectory of the process to be controlled. Any deviation from the desired trajectory path should be corrected by modifying the rule or rules responsible for the undesirable performance. The performance index functions act as an evaluation criterion of the controller performance. In general terms, it measures the deviation from the desired trajectory and issues the appropriate correction to the rule that gave the present behavior. It is derived from linguistic conditional statements by means of using standard fuzzy operations and written in a look-up table form. However, the performance functions are only to show two-dimensional table [7-9], which are difficult to present for two input variables. In this paper, we propose a novel method for decomposing a m-input/n-output SOFLC structure to many 2-input/1-output sets, after which performance index rules in two-dimensional space can be established.

Therefore, SOFLCs have advantages in dealing with infusing anesthetics system and have proved to be strong contenders for application in different forms of control [10]. The main merit is the possibility of implementing a multivariable control system without the need for extensive dynamic models of the process [11,12]. In recent years, there have been some studies on applying SOFLC to biomedical systems, such as muscle relaxation [13-15], depth of anesthesia [16,17], and patient analgesia control [18]. Furthermore, in previous studies, controlling anesthesia in operating theaters using multivariable SOFLC structure has been simulated successfully [2,19]. However, SOFLC has some shortcomings, such as the choice of relevant scale factors prior to fuzzification, and subsequent to defuzzification for different set points [20]. The SOFLC rule bases in previous studies were established with absolute outputs for a specific set points, so the controller using that set of rule bases and scaling factors could only control systems to a designated set point. If the set points change, the rule bases need to be updated and new scaling factors should be set. The scaling factors should be modified such that the controller approximates other set points. However, the human body is a highly nonlinear system, and it is difficult to find a unique scale factors.

In the operating theatre, rapid anesthesia can be achieved by administering the patient a large bolus of drug. Simulation studies showed that administering a bolus and initiating self-organizing rule-based controller can lead to instability [19]. Such regime needs the system to be stabilized first using fixed FLC with absolute control action, hence fixed FLC incremental output, and finally SOFLC with incremental output. In this study, this system has been implemented to control unconsciousness and muscle relaxation. Noise is a very common phenomenon in the data that are usually collected from the human body. This phenomenon exists in the data collected from the electromyogram and blood pressure monitor. Therefore it is important to test the controller under noisy signal conditions by incorporate random noise in the simulation system. Hence, this study had three objectives. The first was to propose a novel method to decompose an m-input/n-output SOFLC structure to many 2-input/1-output sets and to test it using the anesthesia model. The second was to establish a combinative anesthesia FLC and SOFLC structure for controlling anesthetic administrations at different set points. The third objective was to test the controller robustness by incorporating noise signal into the simulation system.

2. Simulation methods

2.1 Simulation model

Modern general anesthesia comprises the triad of muscle relaxation, unconsciousness, and analgesia. Because analgesia is mainly concerned with postoperative conditions, it was not considered in this simulation. Therefore, in this simulation, the measurements of muscle relaxation and unconsciousness were used as the inputs for the controllers. To measure these data, as the anesthetists’ most reliable guides in general, electromyogram (EMG) signal and blood pressure were chosen as the measurements of muscle relaxation and unconsciousness [21-24].

The most common anesthesia drug, atracurium, was chosen for controlling muscle relaxation, and isoflurane was chosen for controlling blood pressure. Regarding the influence of atracurium on blood pressure, investigation had found that it was so small that it could be ignored in the dynamic model [25]. On the other hand, the interaction of isoflurane with muscle relaxation is small but still needs to be considered. By means of pharmacokinetics and pharmacodynamics, mathematical models have been developed for describing the drugs’ effects in human body [25,26]. The overall model is shown in Eq. (1).

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

(1)

where

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

(the atracurium mathematical model),

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

(the interactive component model),

$$G_{22}(s) = \frac{-15.0e^{-0.4s}}{(1+2s)}$$

(the isoflurane unconsciousness model).

$U_1$ is the atracurium infusion.

$U_2$ is the isoflurane concentration.

2.2 Controller design

The SOFLC is a two-level hierarchical controller. The basic level is a simple FLC system, 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. Furthermore, to handle the performance indices of self-organizing and rule-bases in multidimensional space, a concept called the decomposition of SOFLC has been introduced in [2] and been applied in [19] and this paper. The steps for decomposing an $m$-input/$n$-output system into 2-input/1-output sub-systems are described as follows:

(1) 2-input-combinations are taken from the $m$-input set for $n$-outputs.

(2) The rules for controlling each output are established according to each set of 2-input conditions.

(3) The final output can be the union or intersection of the outputs from each sub-system.

(4) According to this decomposition method, the number of 2-input/1-output sub-systems will be $n \times \binom{m}{2}$.

According to the above steps, expert experiences (i.e., initial fuzzy rules) would be more easily transferred into control rules in 2-input/1-output spaces. Gupta et al. [27] proposed a method to decompose a multivariable FLC into many 1-input/1-output FLCs, and proved that the existing error from this decomposition could be neglected in many practical cases. In this study, in order to establish linguistic 2-input/1-output control rules, a multivariable SOFLC system was decomposed into many 2-input/1-output SOFLC sub-systems. The reason for this decomposition is that the performance index of SOFLC in 2-input/1-output spaces is much more easily and simply defined according to the original paper [7]. Hence, the existing error from this decomposition can be compensated via the supervision of self-organizing system according to the controller performance if this performance is defined right. Figure 1 is a decomposed $m$-input/$n$-output SOFLC structure diagram and illustrates how the concept works.

In the previous studies [2,19], the controller was designed with absolute outputs. Figure 2 shows a simple structure diagram of absolute-output SOFLC. The outputs of the controller were the absolute value of anesthetics, and the rule bases were established for the specific set points. Therefore, one set of scaling factors could only apply to one set of set points (e.g., muscle relaxation 80% and blood pressure 110 mmHg). If the set points need to be changed, a new set of scaling factors need to be calculated, or the rule bases should be updated. Hence, in order to extend the set points range, an integration output structure was adopted in this study. A simple structure diagram of integration output SOFLC is shown in Fig. 3. The controller will be able to adjust the anesthetic magnitudes to a suitable level of anesthetics at different set points.

FLC contains four essential elements, namely control rules, membership functions, fuzzy inference engine and defuzzification. The controller inputs are the error of muscle relaxation (i.e., $M_e$), the derivative error of muscle relaxation (i.e., $M_{e-d}$), the error of blood pressure (i.e., $B_e$), and the derivative error of blood pressure (i.e., $B_{e-d}$), while the outputs are the change of atracurium infusion rate (i.e., $d_{\text{Atra inf}}$) and the change of isoflurane concentration (i.e., $d_{\text{ISO conc}}$). In order to fuzzify the inputs and outputs, the

![Figure 1. Decomposition of SOFLC for m-input / n-output.](image1)

![Figure 2. Block diagram of absolute output SOFLC.](image2)

![Figure 3. Block diagram of integration output SOFLC.](image3)
Figure 4. The basic domains of real values in applications, fuzzy domains of linguistic levels, and the fuzzy sets for the inputs and outputs (a) for the input $M_e$ (b) for the input $B_e$ (c) for the input $M_e_d$ (d) for the input $B_e_d$ (e) for the output $d_{Atra_{inf}}$ (f) for the output $d_{Iso_{conc}}$.

Figure 5. The closed-loop SOFLC anesthesia control system.

inputs (i.e., $M_e$, $M_e_d$, $B_e$ and $B_e_d$) were divided into seven levels (the membership functions of inputs), namely negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), and positive big (PB). The outputs (i.e., $d_{Atra_{inf}}$ and $d_{Iso_{conc}}$) were divided into five levels (the membership functions of outputs), namely negative big (NB), negative small (NS), zero (ZE), positive small (PS), and positive big (PB). In this study, the shapes of membership functions were designed as triangular, with 25% overlap. Figure 4 illustrates the basic domains of real values in applications, fuzzy domains of linguistic levels, and the fuzzy sets for the inputs and outputs. Figure 5 shows the closed-loop control structure of the anesthesia system, and the decomposed structure of 4-input/2-output SOFLC with integration output is shown in Fig. 6. According to trial-and-error method, controlling the changes of atracurium infusion and isoflurane concentration had six simple fuzzy rule bases and performance indices for self-organizing of each twenty-five rules for six input combinations (i.e., $M_e$ to $B_e$, $M_e_d$ to $M_e$, $B_e_d$ to $B_e$, $M_e_d$ to $B_e$, $B_e_d$ to $M_e$, and $M_e_d$ to $B_e_d$) which were developed to control this anesthesia system, as shown in Figs. 7 and 8.
Figure 6. Decomposed structure of 4-input / 2-output SOFLC with integration output (M_e is the error of muscle relaxation; M_e_d is the derivative error of muscle relaxation; B_e is the error of blood pressure; B_e_d is the derivative error of blood pressure; d_Atra_inf(t) is the change of atracurium infusion rate; d_Iso_conc(t) is the change of isoflurane concentration; Atra_inf(t-1) is the previous (t-1) atracurium infusion rate; Iso_conc(t-1) is the previous (t-1) isoflurane concentration; Atra_inf(t) is the present (t) atracurium infusion rate which is the sum of d_Atra_inf(t) and Atra_inf(t-1); Iso_conc(t) is the present (t) isoflurane concentration which is the sum of d_Iso_conc(t) and Iso_conc(t-1)).

Figure 7. Basic rule-bases of the SOFLC for anesthesia control: (a) for the output Atracurium infusion rate; (b) for the output Isoflurane concentration (NB means negative big; NM means negative medium; NS means negative small; ZE means zero; PS means positive small; PM means positive medium; PB means positive big; The meanings of M_e, M_e_d, B_e, B_e_d, d_Atra_inf, and d_Iso_conc are the same as those in Fig. 6).
Previous study [19] showed that using a simple FLC before switching to self-organizing structure could prevent instability when a bolus of drug was introduced into the system. Similarly, in this study, a combination of FLC and SOFLC was used.

2.3 Initial bolus

A bolus is a large dose of drug initially given by anesthetists to the patient to achieve rapid anesthesia in a relatively short time. In this study, the drug atracurium was used for achieving the muscle relaxation during the operation. The muscle relaxation was normalized over a scale of 0-1, while the atracurium bolus was set to be about ten times the infusion rate that is usually administered for muscle relaxation, at 0.8 (normalized scale), and infused for five minutes.

2.4 Noise signal

For incorporating the signal noise into the simulations for testing the robustness of the controllers, average noise levels were estimated for muscle relaxation and blood pressure data from fifteen patients. These data were collected over the full time of the different performed operations. The data is shown in Table 1 and shows that there were about 10.95% standard deviation of mean value noise for muscle relaxation and 12.4 mmHg standard deviation of mean value noise for blood pressure.

3. Simulation results

In this study, the integration output SOFLC was established first, then simulated using the patient model. The results are presented in two parts, first part shows the simulation results that incorporate bolus and noise for the purpose of investigating the robustness of the controller. Each simulation was run for 30,000 intervals, 100 intervals present 1 minute. Muscle relaxation was normalized over a scale of 0-1. The initial values of muscle relaxation and blood pressure of the model in simulations were set at 0 normalized scale and 120 mmHg, respectively.

3.1 SOFLC with bolus but without noise

3.1.1 3-stage controller

In previous study [19], anesthesia system control that incorporated an initial bolus and SOFLC was simulated. In that study, it had been found that due to the initial bolus, there was instability in the system, and there were many unnecessary rules being generated, causing the model parameters to deviate

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**Table 1.** The averages and standard deviations of the clinical data of 15 patients for presenting noise amount during surgical operations.

<table>
<thead>
<tr>
<th>Patient</th>
<th>Muscle relaxation (%)</th>
<th>Blood pressure (mm Hg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90.22 (±) 9.83</td>
<td>84.60 (±) 5.66</td>
</tr>
<tr>
<td>2</td>
<td>89.33 (±) 12.43</td>
<td>74.96 (±) 6.72</td>
</tr>
<tr>
<td>3</td>
<td>89.38 (±) 6.96</td>
<td>113.03 (±) 12.94</td>
</tr>
<tr>
<td>4</td>
<td>91.04 (±) 9.97</td>
<td>89.02 (±) 11.95</td>
</tr>
<tr>
<td>5</td>
<td>89.05 (±) 10.43</td>
<td>86.05 (±) 13.35</td>
</tr>
<tr>
<td>6</td>
<td>90.82 (±) 11.99</td>
<td>90.44 (±) 16.45</td>
</tr>
<tr>
<td>7</td>
<td>91.65 (±) 11.68</td>
<td>92.29 (±) 10.69</td>
</tr>
<tr>
<td>8</td>
<td>90.85 (±) 12.82</td>
<td>98.21 (±) 17.71</td>
</tr>
<tr>
<td>9</td>
<td>89.04 (±) 7.49</td>
<td>90.81 (±) 23.23</td>
</tr>
<tr>
<td>10</td>
<td>87.33 (±) 10.34</td>
<td>90.33 (±) 10.31</td>
</tr>
<tr>
<td>11</td>
<td>86.63 (±) 18.09</td>
<td>88.48 (±) 12.05</td>
</tr>
<tr>
<td>12</td>
<td>91.41 (±) 7.40</td>
<td>96.04 (±) 7.43</td>
</tr>
<tr>
<td>13</td>
<td>89.03 (±) 9.32</td>
<td>93.05 (±) 10.64</td>
</tr>
<tr>
<td>14</td>
<td>89.10 (±) 15.68</td>
<td>89.60 (±) 9.26</td>
</tr>
<tr>
<td>15</td>
<td>90.46 (±) 9.78</td>
<td>86.34 (±) 17.69</td>
</tr>
<tr>
<td>Average</td>
<td>89.69 (±) 10.95</td>
<td>90.88 (±) 12.40</td>
</tr>
</tbody>
</table>
from the set point. Using SOFLC with bolus effect would cause steady-state error. Therefore, using simple FLC after the initial bolus could stabilize the system before switching on SOFLC for maintenance. In this simulation, the 3 stages started with an initial bolus, then FLC (integration output) was activated when the muscle relaxation reached the set point, and finally SOFLC (integration output) was switched on at 40 min when the system had reached a stable condition. In this design, the initial atracurium was set to 0.5 to keep up with the bolus effect, because of the slow response from the integration output. Figure 9 shows the simulation results for SP_M = 0.8 and SP_B = 110, and the controlling results were very close to the set points. However for the conditions of SP_M = 0.9 and SP_B = 100, there was a small steady state error, as shown in Fig. 10. The integration squared errors of these two control simulations are listed in Table 2.

Table 2. The integration square error in muscle relaxation and blood pressure of controlling anesthesia with bolus but without noise, where the 3 stages are not any control, FLC (integration), and SOFLC (integration), the 4 stages are not any control, FLC (absolute), FLC (integration), and SOFLC (integration) (Ise_m is the integration square error of muscle relaxation; Ise_b is the integration square error of blood pressure).

<table>
<thead>
<tr>
<th>Set points (M, B)</th>
<th>Controller</th>
<th>Ise_m</th>
<th>Ise_b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9, 110</td>
<td>SOFLC (integration)</td>
<td>34.57</td>
<td>569.84</td>
</tr>
<tr>
<td></td>
<td>FLC (absolute)</td>
<td>22.86</td>
<td>163.19</td>
</tr>
<tr>
<td></td>
<td>&amp; SOFLC (integration)</td>
<td>25.14</td>
<td>569.84</td>
</tr>
<tr>
<td>0.8, 110</td>
<td>SOFLC (integration)</td>
<td>15.00</td>
<td>164.76</td>
</tr>
<tr>
<td></td>
<td>FLC (absolute)</td>
<td>25.14</td>
<td>569.84</td>
</tr>
<tr>
<td></td>
<td>&amp; SOFLC (integration)</td>
<td>15.00</td>
<td>164.76</td>
</tr>
</tbody>
</table>

3.1.2 4-stage controller

In the 3-stage controller method, the initial drug infusion rate needs to be set manually to a specific value. For automatic setting, the 4-stage controller is based on starting the controller with a fixed FLC (absolute output), then switching to an integration output controller after the muscle relaxation reaches the set point, and finally switch to SOFLC after the system reaches to steady state. In this 4-stage design, the switching times were different from the switching times in the 3-stage design. The purpose of employing a fixed FLC (absolute output) is to automatically give initial values of drugs, so it only needs to switch on for a short time. Therefore, the controller was switched to the FLC (integration output) when the drug infusion rate had become enough at 25 min. The time interval between FLC (integration output) and SOFLC in the 3-stage design was 25 min, so we switched the controller to SOFLC at 50 min when the system had reached a stable condition. By this 4-stage design, we automatically controlled the anesthesia system in the simulations. The results at SP_M = 0.8 – SP_B = 110 and SP_M = 0.9 – SP_B = 100 are shown in Figs. 11 and 12, respectively. The integration squared errors of the control simulations are listed in Table 2.

3.2 SOFLC with bolus and noise

In the section 3.1.2, a 4-stage controller was developed and achieved a good control performance. The next step was to test the robustness of this controller design. Figure 13 shows the system under control using the 4-stage controller with noise contamination. The results at SP_M = 0.8 – SP_B = 110 gave an acceptable error, as reported in Table 3.
Figure 11. Simulation of anesthesia system with bolus using 4-stage control at SP_M=0.8, SP_B=110. FLC (absolute) was switched on when muscle relaxation reached the set point, and the switching points of FLC (integration) and SOFLC were at 25 min and 50 min, respectively. (a) Muscle relaxation output; (b) Blood pressure output; (c) Atracurium input; (d) Isoflurane input.

Figure 12. Simulation of anesthesia system with bolus using 4-stage control at SP_M=0.9, SP_B=100. FLC (absolute) was switched on when muscle relaxation reached the set point, and the switching points of FLC (integration) and SOFLC were at 25 min and 50 min, respectively. (a) Muscle relaxation output; (b) Blood pressure output; (c) Atracurium input; (d) Isoflurane input.

Figure 13. The simulation of anesthesia system with bolus and noise using 4-stage control at SP_M=0.8, SP_B=110. FLC (absolute) was switched on when muscle relaxation reached the set point, and the switching points of FLC (integration) and SOFLC were at 25 min and 50 min, respectively. (a) Muscle relaxation output; (b) Blood pressure output; (c) Atracurium input; (d) Isoflurane input.

Table 3. The mean values of muscle relaxation and blood pressure under noise conditions.

<table>
<thead>
<tr>
<th>Set points (M, B)</th>
<th>Controller</th>
<th>$I_{se}$ muscle relaxation (normalized scale)</th>
<th>$I_{se}$ blood pressure (mm Hg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9 , 100</td>
<td>3-stage controller</td>
<td>1.35</td>
<td>3271.9</td>
</tr>
<tr>
<td>0.9 , 100</td>
<td>4-stage controller</td>
<td>0.53</td>
<td>2300.40</td>
</tr>
<tr>
<td>0.8 , 110</td>
<td>3-stage controller</td>
<td>0.07</td>
<td>544.63</td>
</tr>
<tr>
<td>0.8 , 110</td>
<td>4-stage controller</td>
<td>0.35</td>
<td>151.87</td>
</tr>
</tbody>
</table>

3.3 4-stage SOFLC with bolus and noise: initial and modified rule-bases

The initial control rule bases shown in Fig. 7 were derived from trial-and-error method or from discussing with medical experts. Although the derivation of fuzzy rules is a common bottleneck in the application of initial rule bases of the multivariable SOFLC, it is still easy to determine the extreme cases of rules. However, in gray areas such as in the middle of fuzzy sets, it is more difficult to decide based on experts’ experience because the decision may strongly depend on each individual patient. Although experts can still decide some initial rules in this gray area, they may not be optimal to control the anesthesia of a patient in the operating theatres, and some of the rules need to be modified due to inter-patient variations. Hence, this could be done by a multivariable SOFLC algorithm to further fine-tune these rule bases. Multivariable SOFLC has a learning algorithm and is capable of generating and modifying control rules based on an evaluation of the system’s performance. The generation and modification of 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 (i.e. performance index, as shown in Fig. 8) is obtained from a fuzzy algorithm that defines the desired performance linguistically and has the same form as the control algorithm of the generic FLC [8]. Hence, in real-time control, the initial rule bases in Fig. 7 will be modified and generated once for each sampling time of simulation. In order to prove that the rules could be generated and modified, we extracted the final results of rules for simulation of 300 min in section 3.2, as shown in Fig. 14. The modified two rules are: 1st rule: if $M_e$ is $NM$ and
B_e is NM then d_Atra_Inf is PS (i.e., instead of initial PB); and 2nd rule: if M_e_d is PS and B_e is PS then d_Iso_conc is PB (i.e., instead of initial PS). Moreover, many rules were generated for atracurium infusion and isoflurane concentration controls, as shown in the italic and bold rules in Fig. 14.

3.4 The evaluation of controller performance during real-time control

After testing the anesthesia control system, the 4-stage decomposed SOFLC had the best performance. In order to test the speed of this 4-stage decomposed SOFLC algorithm, it took an execution time of 23.68 sec to simulate the anesthesia control with bolus and noise for 300 min (time interval = 0.01 min, i.e., total 30,000 intervals) in an operation. The simulations were carried out by a personal computer with dual-core 2.2 GHz CPU. So, each interval for 0.01 min (0.6 sec) only cost around (23.68/30000 = 0.0008 sec) to calculate this 4-stage decomposed SOFLC algorithm. Therefore, this algorithm can cope with real-time control without delay during practical applications in the operation room.

4. Conclusions

In this paper, the performance of the method to decompose a multivariable SOFLC system into many 2-input/1-output SOFLC sub-systems was verified by the successful anesthesia control simulations. Different FLC structures were tested for controlling a multi-variable anesthesia system. It has been demonstrated that the use of a fixed output FLC (integration output) can achieve good control of the system with small steady state errors for different set-points, however, it has a very slow response time, and it can take a long time for the system to reach the set-point. On the other hand, using a fixed FLC (absolute output) can give a rapid system response, which is required for improving the slow behavior of the integration outputs controller, but it usually controls the system with steady state errors for different set-points. Improving the response of the integration output controller can be achieved by the use of a drug bolus. The drug bolus is considered as an external disturbance to the control system, which affects its performance dramatically. An adaptive controller like the SOLFC can improve the controller performance by changing the rule base in order to adapt itself with the new environment. Therefore a multi-stage controller can be the solution. In this research, it has been demonstrated that controlling the system can be achieved with a drug bolus then switching to a fixed FLC (absolute output) in the 2nd stage, can stabilize the system after the bolus effect. Then switching to a fixed FLC (integration output) can reduce the steady state error, and finally switching to the SOFLC can maintain the system even when the system dynamics are changed during the operation. This study has demonstrated the feasibility and applicability of the multi-stage FLC for anesthesia control. Further clinical trials can improve and refine the system.

References


