The Intelligent Simulation in Inhalational Anaesthesia

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Abstract: - Anesthesia is the art or science of removing sensation of, and reaction to, a surgical procedure. In order to simulate the whole operation during inhalational anaesthesia, a hierarchical architecture for the monitoring and control DOA includes four blocks, which are monitoring DOA, drug controller, patient model, and vaporizer model. The first block focuses on monitoring DOA using the electroencephalograph (EEG) signals (i.e. bispectral index), end-tidal anesthetic agents (Etaa), systolic arterial pressure (SAP) and heart rate (HR) according to fuzzy model. Block 2 is a drug controller that controls the drug infusion to the patient according to a fuzzy logic controller. In the third block, a four-input and four-output artificial neural network has been designed for patient model. In the fourth block, a single input and output artificial neural network has been designed for vaporizer model. Finally, according to the 13 patients' simulation of different set points of DOA (defined from 0 ~ 100), the average of drug consumptions of set point of DOA in 50 (i.e., anaesthetic ok), 30 (i.e., anaesthetic small deep), and 10 (i.e., anaesthetic deep) is 0.93±0.25 , 0.69±0.24, and 0.74±0.21 %, respectively. When compared with the routine clinical trials (i.e., 0.69 ±0.30 %) using desflurane drugs, the set point of DOA in 30 is more close to clinical trials. We conclude that the routine clinical trials are always controlled DOA in 30 which is used less drugs than DOA in 50. After this successful simulation results, the anaesthetists will have confidence to perform on-line automatic control of drugs in the operating theatre.

Key-Words: - Depth of anaesthesia, inhalational anaesthesia, electroencephalograph signals, bispectral index, fuzzy model, fuzzy logic controller, artificial neural network.

1 Introduction

Within the current interest in intelligent engineering, there are 3 broad categories of paradigm which are being actively pursued. They are fuzzy logic, neural networks and genetic algorithms. Each of these paradigms has particular advantages, but with accompanying limitations, both theoretically and practically. The area of anaesthesia systems appears to be an ideal candidate for this approach, because of biological complexity, patient-to-patient variability and difficulties in measurement. Hence, it is timely to explore synergetic coupling between the various intelligent paradigms to apply in inhalational anaesthesia.

Simulations are very important in the aircraft industry where they have been used for many years to train pilots on the ground, thus preventing damage to aeroplanes and loss of life. Similarly, in the nuclear power industry, simulations and training devices have been used for many years to maintain the efficiency and proficiency of their operators. Such simulations rely heavily on powerful computers. Only in recent years have suitable computers and software tools become available to make simulation in anaesthesia feasible and more widely available. Potentially, simulations could provide anaesthesia training to practice at any level of difficulty. Instead of waiting until disaster strikes, anaesthetists will be able to develop their skills in anticipating disasters and to practice treatments. The simulation allows the disaster to be repeated many times for the anaesthetist to develop skills under optimum interactive learning conditions, without endangering patients [1].

Anaesthesia is the art or science of removing sensation of, and reaction to, a surgical procedure. Anaesthesia means loss of all sensation whether it is a sense of pain, touch, temperature or position. Modern general anesthesia comprises the triad of muscle relaxation, unconsciousness, and analgesia (i.e. pain relief). The first role of the measurement of muscle relaxation (or drug-induced paralysis) is considerably easier and the third role is mainly concerned with postoperative conditions and these two roles will be not described in this paper. However, the second role related to depth of anaesthesia (i.e., unconsciousness) is much harder to define and not readily measurable. In practice,

anaesthetists have a number of clinical signs and on-line measurements which can be used selectively for the determination of the patient's state [2]. In order to simulate the whole operation during inhalational anaesthesia, a hierarchical architecture for the monitoring and control DOA using intelligent model and control is proposed in this paper included four blocks, which are monitoring DOA via fuzzy model, drug controller via fuzzy logic controller, patient model and vaporizer model via artificial neural networks.

2 A hierarchical structure for the monitoring and control DOA

According to Mesarovic et al. in 1970 [3], a hierarchical system contains some essential characteristics, i.e. vertical arrangement of subsystems, right of intervention of the higher levels, and performance interdependence of the lower levels. Hence, a hierarchical architecture for the monitoring and control DOA included four blocks, which are monitoring DOA, drug controller, patient model, and vaporizer model is shown in Fig. 1. The first block focuses on monitoring DOA using the electroencephalograph (EEG) signals (i.e. bispectral index, BIS), end-tidal anesthetic agents (Etaa), systolic arterial pressure (SAP) and heart rate (HR) according to fuzzy model. Block 2 is a drug controller that controls the drug infusion to the patient according to a fuzzy logic controller. In the third block, a four-input and four-output artificial neural network has been designed for patient model. In the fourth block, a single input and output artificial neural network has been designed for vaporizer model.

2.1 Block 1) Monitoring the DOA

Recently, the electroencephalograph (EEG) signals (i.e. bispectral index) has been approved that they related to unconsciousness more closely than cardiovascular indicators. Hence, the first level estimates of DOA from online bispectral index and end-tidal anesthetic agents (Etaa) are defined as a primary DOA (PDOA). The second level is focused on measuring cardiovascular signals, such as systolic arterial pressure (SAP) and heart rate (HR) to obtain an estimate of a secondary DOA (SDOA). Hence, using the first level and second level, we fuse these two factors using fuzzy model to decide the DOA. More details have been published in Shieh et al. [4].

2.2 Block 2) Controller design for drug infusion

A simple fuzzy logic controller was designed in this system for regulating unconsciousness. The two input variables were chosen to be error and change in error for DOA, while the one output was the drug controller output. The fuzzy sets were formed on a discrete support universe of 5 elements for each input and output variable. The shape of membership function was chosen to be triangular and the rules were discussed with anaesthetists as shown in Table 1. These lingusitic rules were transformed into a lookup table, as shown in Table 2, using standard techniques of fuzzy calculus.

The inference engine works by using Gupta et al's [5] method which involves the decomposition of multivariable fuzzy system into a set of one-dimensional systems. The input, output variable and fuzzy relations are described by the following equation:

$$\mathbf{Y}_j = \bigwedge_{i=1}^{m} (\mathbf{X}_i \circ R_{ij}) \qquad (1)$$

$$R_{ij} = \bigvee_{k=1}^{p} [\mathbf{X}_i(k) \wedge \mathbf{Y}_j(k)] \qquad (2)$$

where Xi is the fuzzy value of the i-input variable; Yj is the fuzzy value of the j-output variable; Rij is the fuzzy relation of the i-input and j-output variable; m are the number of input variables; n are the number of output variables; p are the number of rules; $\circ$ is the max-min composition; $\wedge$ is the min operator; $\vee$ is the max operator.

Finally, a single value output is produced using the defuzzification procedure based on centra of area (COA) followed by scaling to a real value.

2.3 Block 3) Patient model

Artificial neural networks offer a better possibility of rapid knowledge acquisition via their self-organizing learning properties. They have the ability to learn in those cases where it is possible to specify the inputs and outputs but difficult to define the relationship between them. They are also tolerant to noise in the input data. These attributes of ANNs are suitable for the domain of anaesthesia because the relationships between clinical signs are not clear. Back-propagation (BP) is the most popular learning rule among researchers suggested. However, the BP cannot deal with the time series problems of biomedical signals. Hence, a recurrent neural network has been popularly used for dealing with these problems. These networks are basically back-propagation networks with proper feedback links. In other words, the connections in the partially recurrent networks are mainly feedback but include a carefully chosen set of feedback connections.

Hence, in this study, the Elman network [6] has been used to train the patient model with four inputs (i.e., fractional inspired anaesthetic gas (Fiaa), gender, age and weight) and four outputs (i.e., BIS, Etaa, SAP and HR) as shown in block 3 of Fig 1. Also, we use a four-layer artificial neural network with one input layer having five input nodes (i.e., four input nodes and one bias node) and twenty-one recurrent nodes (i.e., twenty hidden nodes and one bias node from first hidden layer), two hidden layers having each twenty hidden nodes and one bias node, and one output layer having four output nodes as shown in Fig. 2.

The network must first be trained. When an input is presented to an untrained network, a random output is produced. An error function (i.e., cost function) is defined, that represents the difference between the network's current output and the actual output. To get the desired output, the value of the error function is continually reduced by adjusting the weights of the links between the nodes. This is done by propagating the error value for each actual output backwards to the hidden layer. The adjustments for the weights in the hidden layer are calculated using the derivatives of the error functions that are used to adjust the weights for the output layer nodes. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize the error function.

2.4 Block 4) Vaporizer model

In this study, the desflurane gas flow through the vaporizing chamber determines the concentration of anaesthetic agent delivered to the patient. The greater the flow, the larger the amount of vapor produced. Normally, desflurane gas flow is regulated by turning the dial to position the rotary valve by anaesthetists. This increases or decreases the resistance in this flow channel. In order to automatic recording the position of the rotary valve for each regulation, a robot machine was designed to record and control the turning the dial via a notebook computer. Then, the desflurane gas from the vaporizer leave the machine outlet, enter the absorber (fresh gas) inlet, flow through the inhalation check valve into the breathing circuit, and joins the fresh gas going to the patient. There is an infrared sensor to monitor the fractional inspired anaesthetic gas (Fiaa) into the patient. In order to model the relation between the position of the rotary valve and the Fiaa, we also use a four-layer Elman network structure with one input layer having two input nodes (i.e., one input node and one bias node) and five recurrent nodes (i.e., four hidden nodes and one bias node from first hidden layer), two hidden layers having each four hidden nodes and one bias node, and one output layer having one output node.

3 Patients and methods

Thirteen adult American Society of Anesthesiologist (ASA) physical status 1 or 2 patients undergoing general anaesthesia, were studied during inhalational anaesthesia using desflurane anaesthetic gas. All patients received a standardized anaesthetic. Patients were excluded if they had clinical evidence of severe respiratory, cardiovascular, hepatic, renal or endocrine disease, uncontrolled hypertension, or previous adverse response to general anaesthesia. Patients were also excluded if they had a history of any neurologic or psychiatric disorders, or if they were taking any drugs likely to influence the course of anaesthesia.

The whole system was programmed in language “Borland C++”. An IBM compatible notebook was used for collection, display, and storage of data as shown in Fig. 3. The digital communication was done via RS232 serial port which was interfaced to the Datex AS/3 and Model A-1050 Spectral EEG Monitor (Aspect Medical Systems, Natick, MA) for monitoring clinical signs, such as SAP, HR , Etaa and BIS. The AS/3 was set to provide arterial pressure, heart rate, information at 3-min intervals. The bispectral index was recorded continuously during induction, maintenance and recovery stages using a Model A-1050 Spectral EEG Monitor. The BIS is a variable derived from the EEG that has been reported to have the ability to measure the hypnotic component of the anaesthetic state [7]. It is a dimensionless number from 0 to 100, and decreasing values indicate more sedation and hypnosis. However, the whole system was still under supervisory by the anesthesiologist.

4 Simulation results and Conclusion

According to the anaesthesia simulation system in Fig. 1, we integrated the four blocks and simulated the 13 patients with the different set points of DOA. The average of drug consumptions of each set point of DOA in 50 (i.e., anaesthetic ok), 30 (i.e., anaesthetic small deep), and 10 (i.e., anaesthetic deep) is 0.93±0.25 , 0.69±0.24, and 0.74±0.21 %, respectively, compared with the routine clinical trials (i.e., 0.69 ±0.30 %) using desflurane drugs as shown in Table 3. When compared with the routine clinical trials using desflurane drugs, the set point of DOA in 30 is more close to clinical trials.

5 Conclusion

A hierarchical architecture included four blocks for anaesthesia simulation during inhalation has been developed in this paper. According to the simulation results, the routine clinical trials are always controlled DOA in 30 which is used less drugs than DOA in 50. After this successful simulation results, the anaesthetists will have confidence to perform on-line automatic control of drugs in the operating theatre.

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Table 1. The anaesthetist's rule-base for controlling the depth of anaesthesia

				$DOA_{E(now)}$		
		AL (-2)	ASL (-1)	AO (0)	ASD (1)	AD (2)
	AL (-2)	NB	NB	NS	NS	ZO
	ASL (-1)	NB	NS	NS	ZO	PS
$DOA_{CE(now)}$	AO (0)	NS	NS	ZO	PS	PS
	ASD (1)	NS	ZO	PS	PS	PB
	AD (2)	ZO	PS	PS	PB	PB

Table 2. The lookup table for controlling the depth of anaesthesia

				$DOA_{E(now)}$		
		AL (-2)	ASL (-1)	AO (0)	ASD (1)	AD (2)
	AL (-2)	-0.31	-0.31	-0.18	-0.18	0
	ASL (-1)	-0.31	-0.22	-0.1	0	0.08
$DOA_{CE(now)}$	AO (0)	0.18	0.1	0	0.1	0.18
	ASD (1)	-0.08	0	0.1	0.22	0.31
	AD (2)	0	0.08	0.18	0.31	0.31

Table 3. The average of drug consumptions of set point of DOA in 50 (i.e., anaesthetic ok), 30 (i.e., anaesthetic small deep), and 10 (i.e., anaesthetic deep) compared with the routine clinical trials (i.e., raw data)

Patients	Raw data Drug Consumption (%)	Simulation data DOA=50 Drug Consumption (%)	Simulation data DOA=30 Drug Consumption (%)	Simulation data DOA=10 Drug Consumption (%)
pa01	1.04	1.06	0.91	1.02
pa02	1.12	0.75	0.46	0.61
pa03	0.84	0.88	0.66	0.59
pa04	0.58	1.31	1.02	0.96
pa05	1.26	0.99	0.74	0.69
pa06	0.37	0.91	0.71	0.70
pa07	0.44	0.81	0.57	0.79
Pa08	0.34	0.66	0.46	0.39
Pa09	0.43	0.83	0.61	0.73
pa10	0.53	1.53	1.21	1.21
pa11	0.85	0.72	0.54	0.65
pa12	0.64	0.96	0.75	0.67
pa13	0.53	0.65	0.39	0.61
Ave	0.69	0.93	0.69	0.74
SD	0.30	0.25	0.24	0.21

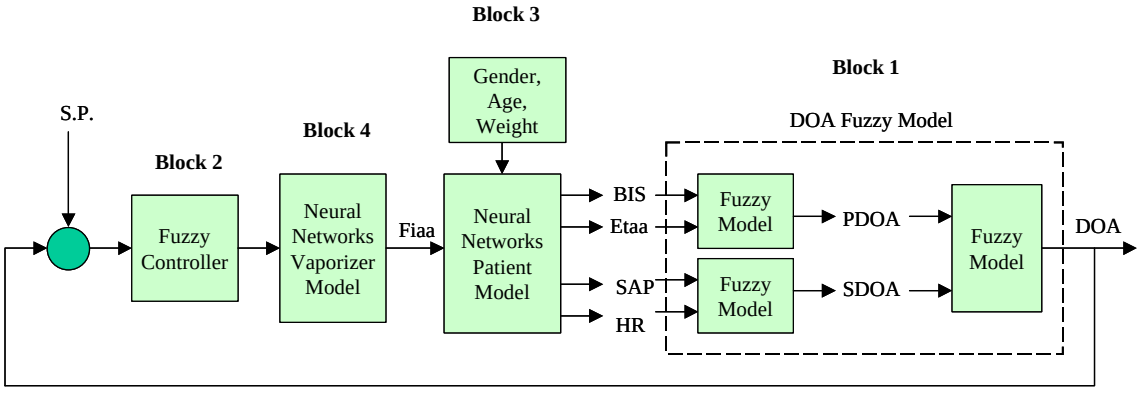

Fig. 1. A hierarchical architecture included four blocks for anaesthesia simulation during inhalation

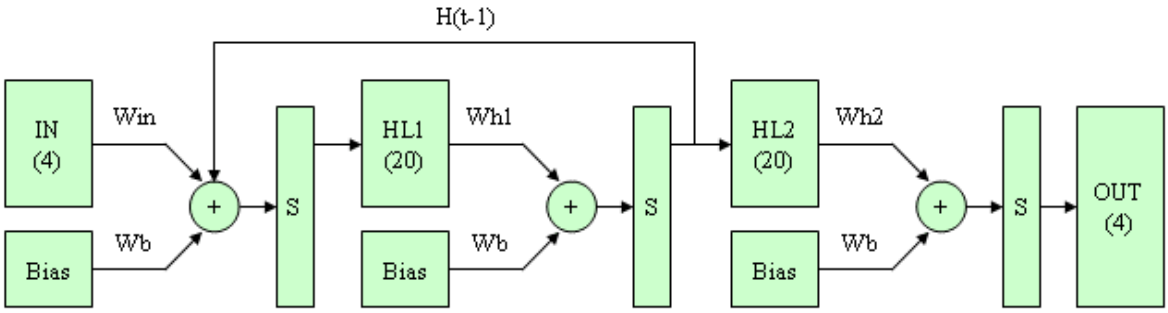

Fig. 2. A four-layer artificial neural network with one input layer having five input nodes and twenty-one recurrent nodes, two hidden layers having each twenty hidden nodes and one bias node, and one output layer having four output nodes

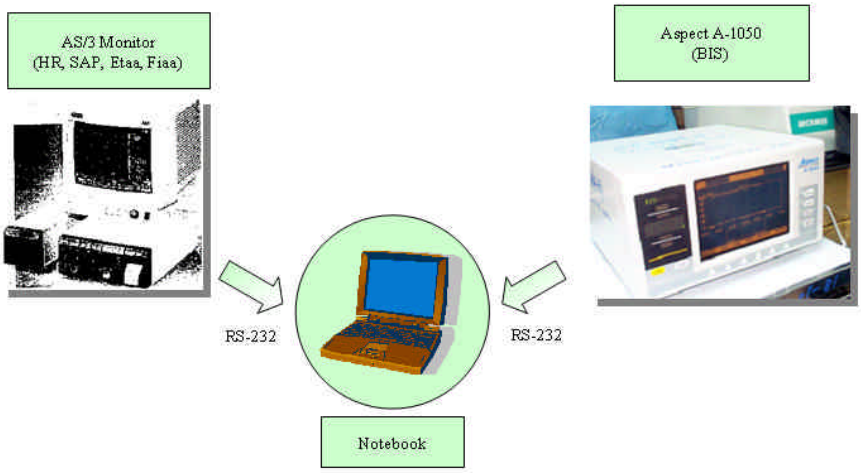

Fig. 3. An IBM compatible notebook for data acquisition of clinical data using serial communication RS232 in the operating theatre