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Interval type-2 fuzzy neural network controller for a multivariable anesthesia system based on a hardware-in-the-loop simulation

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Objective: This manuscript describes the use of a hardware-in-the-loop simulation to simulate the control of a multivariable anesthesia system based on an interval type-2 fuzzy neural network (IT2FNN) controller.
Methods and materials: The IT2FNN controller consists of an interval type-2 fuzzy linguistic process as the antecedent part and an interval neural network as the consequent part. It has been proposed that the IT2FNN controller can be used for the control of a multivariable anesthesia system to minimize the effects of surgical stimulation and to overcome the uncertainty problem introduced by the large inter-individual variability of the patient parameters. The parameters of the IT2FNN controller were trained online using a back-propagation algorithm.
Results: Three experimental cases are presented. All of the experimental results show good performance for the proposed controller over a wide range of patient parameters. Additionally, the results show better performance than the type-1 fuzzy neural network (T1FNN) controller under the effect of surgical stimulation. The response of the proposed controller has a smaller settling time and a smaller overshoot compared with the T1FNN controller and the adaptive interval type-2 fuzzy logic controller (AIT2FLC). The values of the performance indices for the proposed controller are lower than those obtained for the T1FNN controller and the AIT2FLC.
Conclusion: The IT2FNN controller is superior to the T1FNN controller for the handling of uncertain information due to the structure of type-2 fuzzy logic systems (FLSs), which are able to model and minimize the numerical and linguistic uncertainties associated with the inputs and outputs of the FLSs.
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1. Introduction

The type-1 fuzzy neural network (T1FNN) controller combines the capability of fuzzy reasoning to handle uncertain information and the capability of artificial neural networks to learn from processes [1]. These controllers have been successfully applied in many fields [2–4]. The T1FNN controller was introduced to handle the uncertainties found in real systems, but it has been demonstrated to be limited in the handling of the uncertainties of fuzzy membership sets and rule-based type-1 fuzzy logic systems (T1FLSs). Therefore, a type-2 fuzzy set (T2FS) was used.

A T2FS is characterized by a fuzzy membership function (MF) (i.e., the membership grade for each element of this set is a fuzzy set in [0,1]), unlike a type-1 fuzzy set, the membership grade of which is a crisp number in [0,1] [5]. Therefore, a T2FS provides additional degrees of freedom that make it possible to model and handle the uncertainties directly [6]. A type-2 fuzzy logic system (T2FLS) is also characterized by IF–THEN rules, but its antecedent or consequent sets are type-2 sets. A T2FLS can be used when the circumstances are too uncertain to exactly determine the membership grades, and these have been used in many applications, particularly in the control system [7–9]. The interval type-2 fuzzy logic system (IT2FLS) is a special case of the T2FLS [10] in which the IT2FLS is simpler to work with than a general T2FLS and distributes the uncertainty evenly among all admissible primary memberships [11]. The IT2FLS has been applied to various fields with great success [12–17]. The purpose of this study was to develop an interval type-2 fuzzy neural network (IT2FNN) controller that consists of an interval type-2 fuzzy linguistic process as the antecedent and an interval neural network as the consequent. The parameters of the IT2FNN controller were trained using the back-propagation (BP) method to minimize the difference between the desired and actual outputs.

The multivariable anesthetic model, which represents modern general anesthesia, consists of muscle relaxation (MR)

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(i.e., paralysis), unconsciousness (i.e., hypnosis), and analgesia (i.e., pain relief) [18]. Two drugs, namely isoflurane and atracurium, are commonly used for general anesthesia. These drugs elicit the anesthesia and MR signs, which are represented by the mean arterial blood pressure (MABP) and the evoked electromyogram (EMG), respectively [19]. There are two main problems associated with multivariable anesthesia systems [20]. First, the nonlinear structure of the pharmacodynamics representing the relaxant drug behavior may make the MR level saturate with any large control dose. Second, there is great uncertainty inherited from the large inter-individual variability of the patient parameters, and a large delay is associated with this process. Hence, these problems make the multivariable anesthesia system a very challenging one. The T1FNN controller has been previously used to control the anesthesia system [21–24]. The parameters of the T1FNN controller were trained using the BP algorithm. Tosun and Güntürkün [24] tested a T1FNN controller using 10 datasets obtained from four different patients. In our previous work [25], the interval type-2 fuzzy logic controller (IT2FLC) and the adaptive interval type-2 fuzzy logic controller (AIT2FLC) were proposed for controlling the multivariable anesthesia system. Our results showed that the AIT2FLC rather than the IT2FLC is able to respond to the uncertainty introduced by the large inter- and intra-individual variability of patient parameters. In this paper, the IT2FNN controller was proposed for controlling the multivariable anesthesia system. The test was performed using a hardware-in-the-loop (HIL) simulation. The results of the proposed IT2FNN controller were compared with those obtained with a T1FNN controller and an AIT2FLC. The robustness of the IT2FNN controller was expected to provide some performance improvements compared with the performance achieved with a T1FNN controller and an AIT2FLC due to the reduced effects of the inter-individual variability of patient parameters and surgical stimulations.

This paper is organized as follows. In Section 2, the IT2FNN controller is presented. The description of the mathematical model of the multivariable anesthesia system is presented in Section 3. The HIL simulation of the multivariable anesthesia system is described in Section 4. Section 5 details the experimental results, and Section 6 presents the conclusions.

2. IT2FNN controller

Fig. 1 shows a 2-D interval type-2 Gaussian MF with a fixed mean, m, and an uncertain standard deviation in $[\sigma_1, \sigma_2]$. This MF can be expressed as Eq. (1) [26]:

$$\mu_{\tilde{A}}(x) = \exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right], \quad \sigma \in [\bar{\sigma}, \underline{\sigma}] \tag{1}$$

The T2FS is found in a region called the footprint of uncertainty and is bounded by an upper membership and a lower membership, which are denoted $\bar{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x')$, respectively.

The network structure of the IT2FNN controller is shown in Fig. 2. This controller consists of an interval type-2 fuzzy linguistic process as the antecedent and a three-layer interval neural network as the consequent. In the following derivation, the superscripts of all of the symbols shown in Eqs. (2)–(7) represent the number of the layer of the IT2FNN controller. The IF–THEN rule for the IT2FNN controller can be expressed as

$$R_f: \text{IF } x_1^1 \text{ is } \tilde{M}_1^f, \text{ and } x_2^1 \text{ is } \tilde{M}_2^f, \text{ and}\ldots\text{and } x_m^1 \text{ is } \tilde{M}_m^f$$
$$\text{THEN } u_1 \text{ is } \left[w_{Rf}^4, w_{Lf}^4\right] \tag{2}$$

where $f = 1, 2, \ldots, n$ is the rule number, $x_1^1 \ldots x_m^1$ are the inputs of the IT2FNN controller, and $\tilde{M}_1^f \ldots \tilde{M}_m^f$ are the interval type-2 fuzzy sets (IT2FSs) of the antecedent part. $\left[w_{RF}^4, w_{Lf}^4\right]$ is a centroid set with the membership grade of the secondary MF set to unity, which can be called the weighting interval set and is derived from IT2FSs in the consequent partition. This centroid set refers to the collection of centroids from all of the embedded T1FLSs. The IT2FNN controller is introduced as follows in each layer [27]:

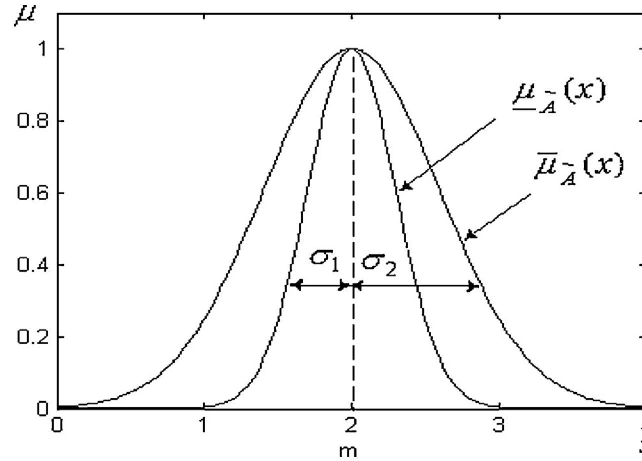

Fig. 1. Interval type-2 fuzzy set with uncertain mean.

(1) *Layer 1 – Input layer*: For every node i in this layer, the node input and the node output are represented as

$$net_i^1(N) = x_i^1, \quad u_i^1 = f_i^1(net_i^1(N)) = net_i^1(N), \quad i = 1, 2 \tag{3}$$

where N denotes the number of iterations.*Layer 2 —Membership layer:* In this layer, each node performs an interval type-2 fuzzy MF, as shown in Fig. 1. For the jth node,

$$u_j^2(N) = \tilde{M}_i^j(x_i^2) = f_j^2(net_j^2(N)) = \exp(net_j^2(N))$$
$$= \begin{cases} \bar{u}_j^2(N) & as \quad \sigma_{ij} = \bar{\sigma}_{ij} \\ \underline{u}_j^2(N) & as \quad \sigma_{ij} = \underline{\sigma}_{ij} \end{cases} \quad j = 1, \ldots, s \tag{4}$$

where $net_j^2(N) = -(1/2)(x_i^2 - m_{ij})^2/(\sigma_{ij})^2$, m_{ij} and σ_{ij} are the mean and the standard deviation, respectively, of the Gaussian MF in the jth term of the ith input linguistic variable x_i^2 to the node of layer 2, and s is the number of the linguistic values with respect to each input node. As shown in Fig. 1, a type-2 MF can be represented as an interval bound by an upper MF $\bar{\mu}_{\tilde{A}}(x)$ and a lower MF $\underline{\mu}_{\tilde{A}}(x)$. Therefore, the output of layer 2, $u_j^2(N)$, is also represented as $\left[\underline{u}_j^2(N), \bar{u}_j^2(N)\right]$.

Layer 3 —Rule layer: Each node k in this layer is denoted by $\prod$ which multiplies the input signals and outputs the result. For the kth rule node, $net_k^3(N) = \prod_j w_{jk}^3 x_j^3(N)$

$$u_k^3(N) = f_k^3(net_k^3(N)) = net_k^3(N) \begin{cases} \bar{u}_k^3(N) = \prod_{j=2}^{n}(w_{jk}^3 \bar{u}_j^2) \\ \underline{u}_k^3(N) = \prod_{j=1}^{n}(w_{jk}^3 \underline{u}_j^2) \end{cases} \quad k = 1, \ldots, n \tag{5}$$

where x_j^3 represents the jth input to the node of layer 3, w_{jk}^3 are the weights between the membership layer and the rule layer and are set to unity to simplify the implementation for real-time control, and n is the number of rules. Similar to layer 2, the output of layer 3 is represented as $[\underline{u}_k^3(N), \bar{u}_k^3(N)]$.

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