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An intelligent fuzzy theory for ocean structure system analysis

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Abstract. This paper deals with the problem of the global stabilization for a class of ocean structure systems. It is well known that, in general, the global asymptotic stability of the ocean structure subsystems does not imply the global asymptotic stability of the composite closed-loop system. The classical fuzzy inference methods cannot work to their full potential in such circumstances because given knowledge does not cover the entire problem domain. However, requirements of fuzzy systems may change over time and therefore, the use of a static rule base may affect the effectiveness of fuzzy rule interpolation due to the absence of the most concurrent (dynamic) rules. Designing a dynamic rule base yet needs additional information. In this paper, we demonstrate this proposed methodology is a flexible and general approach, with no theoretical restriction over the employment of any particular interpolation in performing interpolation nor in the computational mechanisms to implement fitness evaluation and rule promotion.

Keywords: intelligent control function; fuzzy rule interpolation (FRI), interpolated rules

1. Introduction

In recent years, fuzzy logic control (FLC) has been used in many successful practical control applications. Despite the success, it has become evident that many basic issues remain to be further addressed. The idea is to design a compensator for each rule of the fuzzy model. Since each control rule is individually designed from the corresponding rule of the T-S fuzzy model, the linear control design techniques can be employed to design the PDC fuzzy controller (see Omidi and Lotfi 2017, Dinachandra and Raju 2017, Loria and Nesic 2003, Panteley and Loria 1998, Panda *et al.* 2011, Chu and Tsai 2007, Pardhan and Panda 2012, Wang *et al*. 2012, Lam 2009, Liu and Zhang 2003, Park *et al*. 2003, Wang *et al*. 1996).

Fuzzy rule interpolation (FRI) offers the most effective reasoning mechanism to perform fuzzy reasoning offers the most effective reasoning mechanism to perform fuzzy reasoning based on a sparse rule base. The classical fuzzy inference methods cannot work to their full potential in such circumstances because given knowledge does not cover the entire problem domain. However, requirements of fuzzy systems may change over time and therefore, the use of a static rule base

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may affect the effectiveness of FRI due to the absence of the most concurrent (dynamic) rules. Designing a dynamic rule base yet needs additional information. Fortunately, a fuzzy reasoning system that utilizes FRI may produce a large number of interpolated rules during the interpolative reasoning process. Such interpolative results are always discarded once the required outcomes have been obtained in the present applications of FRI. Nonetheless, these relinquished interpolated rules may contain possibly valuable information, covering regions that were uncovered by the original sparse rule base and thus, may be collected and utilized to create a dynamic rule base through generalization.

2. Background

Several methods for evaluating stability designs have been successfully applied, see Cheng *et al*. (2016) and Su *et al*. (2017). Systematic comparative investigations are carried out against conventional FRI that uses just the original sparse rule base, demonstrating that D-FRI possesses higher accuracy and robustness level.

In addition to evaluation of D-FRI against benchmark datasets, it is important to examine how it may work in a real-world application setting. Security is one of the major concerns of any organization regardless of their size and nature of work. Security attacks and their types are countless, however, network intrusion attack is one of the key concerns, being an illicit attempt that compromises the confidentiality, integrity, or availability of the organizational IT infrastructure.

Although there have been many successful applications of intelligent computation, some references of damage assessment and uncertainty analysis were published to mitigate the threaten of casualty, in which the fuzzy theory has received considerable attention recently in structural engineering. This article attempts to expect this future and discusses directions of research to approach the realization of more intelligent systems.

3. Mathematical formulation background

3.1 Initial boundary value problem for ocean structure systems

Consider a wave-induced flow field system in which a Cartesian coordinate system oxz is employed. As shown in the sketch of a 2D numerical wave flume, a plane $z=0$ coincides with the undisturbed still water level and the z-axis is directed vertically upward. The vertical elevation of any point on the free surface can be defined by the function $z=\eta(x,y,t)$, in which the surface tension is negligible. For incompressible fluids the fluid density is constant throughout the flow field. Thus

$$\nabla \cdot \vec{V} = 0 \tag{1}$$

3.2 fuzzy rule based interpolation

For simplicity and owing to their popularity, in this work, fuzzy sets are represented using triangular membership functions. Suppose that an original, sparse rule base $\mathbb{R}$ exists, with rules $R_i \in \mathbb{R}$ and an observation O:

R_i: IF x_i is $A_{i,1}, \ldots,$ and x_j is $A_{i,j}, \ldots,$ and X_N is $A_{i,N}$,

THEN y is B_i

O: $A_{o,1}, \ldots, A_{o,j}, \ldots, A_{o,N}$

where i indexes rule R_i in the sparse rule base, $A_{i,j} = (a_0, a_1, a_2)$ is the triangular linguistic term defined on the domain of the antecedent variable x_j , $j \in \{1, \ldots, N\}$, with N being the total number of antecedents, and B_i is the consequent.

Let a given observed fuzzy value of the variable x_j be denoted by $A_{\circ,j}$, and the representative value rep(A) of a triangular fuzzy set A be defined as the mean of the X coordinates of the triangle's three odd points: the left and right extremities of the support a_0, a_2 (with membership values = 0), and the normal point a_1 (with membership value = 1)

$$rep(A) = (a_0 + a_1 + a_2) / 3$$

The distance between R_i and O is determined by computing the aggregated distance of all antecedent variables

$$d(R_i, O) = \sqrt{\sum_{j=1}^{N} d_j^2}, d_j = \frac{d(A_{i,j}, A_{\circ,j})}{range_{x,j}} \tag{2}$$

where $d(A_{i,j}, A_{o,j}) = \left|rep(A_{i,j}) - rep(A_{\circ,j})\right|$ is the distance between the representative values of the two fuzzy sets in the jth antecedent, with range$_{xj}$ = max$_{xj}$ − min$_{xj}$ over the domain of the variable x_j.$d_j \in [0,1]$ is therefore the normalized result of the otherwise absolute distance measure, so that distances are compatible with each other across different variable domains. The M, $M \geq 2$ rules which have the least distance measurements, with regard to the observed values $A_{o,j}$ are then chosen to perform the interpolation in order to obtain the required conclusion $B_\circ$.

Guided by the new observation, an intermediate rule is needed to approximately approach the final outcome of the consequent, by linearly interpolating the previously identified M closest rules to the observation. The antecedents of this rule are initially estimated by manipulating the antecedents of the M rules

$$A_j^{\dagger\dagger} = \sum_{i=1}^{M} w_{i,j} A_{i,j} \tag{3}$$

where

$$\omega_{i,j} = \frac{w_{i,j}^{\dagger}}{\sum_{k=1}^{M} w_{i,j}^{\dagger}}, \omega_{i,j}^{\dagger} = exp^{-d(A_{i,j}, A_{o,j})} \tag{4}$$

These $A_j^{\dagger\dagger}$ are then shifted to $A_j^{\dagger}$ such that they have the same representative values as those of $A_{o,j}$

$$A_j^{\dagger} = A_j^{\dagger\dagger} + \delta_j range_{x_j} \tag{5}$$

where δ_j is the bias between $A_{o,j}$ and $A_j^{\dagger}$ on the *j*th variable domain

$$\delta_j = \frac{rep(A_{o,j}) - rep(A_j^{\dagger})}{range_{x_j}} \tag{6}$$

From this, the shifted intermediate consequent $B^{\dagger}$ can be computed, with the parameters ω_{B_i} and δ_B being aggregated from those regarding the antecedents of $A_j^{\dagger}$, such that

$$\omega_{B_i} = \frac{1}{N}\sum_{j=1}^{N} \omega_{i,j}, \delta_B = \frac{1}{N}\sum_{j=1}^{N} \delta_j. \tag{7}$$

The above intermediate rule ensures that the representative values of its antecedents are the same as those of the corresponding elements in the given observation. In order to make the fuzzy values in this rule also the same as the observation (so that the observation matches the resulting rule), scale and move transformations will be required.

Thus, guided by the observation, the current support of $A_j^{\dagger}$, ($a_0^{\dagger}$, $a_2^{\dagger}$) is first rescaled to a new support (a_0^{+}, a_2^{+}) such that , $a_2^{+} - a_0^{+} = s_j \times (a_2^{\dagger} - a_0^{\dagger})$

$$\begin{cases} a_0^{+} = \frac{a_0^{\dagger}(1+2s_j)+a_1^{\dagger}(1-s_j)+a_2^{\dagger}(1-s_j)}{3} & (8) \\ a_1^{+} = \frac{a_0^{\dagger}(1-s_j)+a_1^{\dagger}(1+2s_j)+a_2^{\dagger}(1-s_j)}{3} & (9) \\ a_2^{+} = \frac{a_0^{\dagger}(1-s_j)+a_1^{\dagger}(1-s_j)+a_2^{\dagger}(1+2s_j)}{3} & (10) \\ \qquad s_j = \frac{a_2^{+}-a_0^{+}}{a_2^{\dagger}-a_0^{\dagger}} \end{cases}$$

From this, the scaling factor s_B for the consequent can then be calculated by

$$s_B = \frac{\sum_{j=1}^{N} s_j}{N} \tag{11}$$

The resulting rescaled fuzzy values are subsequently moved using the following move rate m_j, so that the final transformed fuzzy sets match the corresponding elements in the observation

$$\begin{cases} m_j = \frac{3(a_0 - a_0^{+})}{a_1^{+} - a_0^{+}}, a_0 \geq a_0^{+} \\ m_j = \frac{3(a_0 - a_0^{+})}{a_3^{+} - a_2^{+}}, \text{otherwise} \end{cases} \tag{12}$$

From this, the move factor m_B for the consequent is calculated such that

$$m_B = \frac{\sum_{j=1}^{N} m_j}{N} \tag{13}$$

The final interpolated result B_o can now be estimated by applying the scale and move transformation to $B\dagger$, using the parameters s_B, and m_B. Note that given both transformations are linear operations, the order of applying the scale and move transformations can be reversed.

The momentum equation obtained from the motion of the floating structure is extensively derived from Newton's second law. Assume that the momentum equation of a ocean structure system can be characterized by the following differential equation (see Ignaciuk and Bartoszewicz (2010), Korkmaz (2011), Kuok and Yuen (2012)

$$M\ddot{\bar{X}}(t) = -M\bar{r}\phi(t) \tag{14}$$

where $\overline{X}(t) = [\bar{x}_1(t), \bar{x}_2(t) \cdots \bar{x}_n(t)] \in R^n$ is an n-vector; $\ddot{\bar{X}}(t)$, $\dot{\bar{X}}(t)$, $\bar{X}(t)$ are the acceleration, velocity, and displacement vectors, respectively. This is only a static model and M is the mass of the system; $M\bar{r}\phi(t)$ is a wave-induced external force which can be expressed as follows

$$M\bar{r}\phi(t) = F_{wx} - F_{TX} \tag{15}$$

where F_{wx} is the horizontal wave force acting on the both sides of the structure; and F_{Tx} is the horizontal component of the static (or the pre-tensioned) tension applied by the tension legs. The static tension is given by $F_{Tx} = f\xi$.

For controller design as proposed by Hammami (2001) and Sun *et al.* (2003), the standard first-order state equation is obtained from Eq. (16) assuming the equation of motion for a shear-type-building modeled by an n-degrees-of-freedom system controlled by actuators and subjected to an external force

$$\dot{X}(t) = AX(t) + E\phi(t) \tag{16}$$

where $X(t) = \begin{bmatrix} \bar{x}(t) \\ \dot{\bar{x}}(t) \end{bmatrix}$, $A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$, $E = \begin{bmatrix} 0 \\ -\bar{r} \end{bmatrix}$, in which $\overline{X}(t) = [\bar{x}_1(t), \bar{x}_2(t) \cdots \bar{x}_n(t)] \in R^n$ is an n-vector; $\ddot{\bar{X}}(t)$, $\dot{\bar{X}}(t)$, $\bar{X}(t)$ are the acceleration, velocity, and displacement vectors, respectively; matrices M, C, and K are $(n \times n)$ mass, damping, and stiffness matrices, respectively; $\bar{r}$ is an n-vector denoting the influence of the external force; $\phi(t)$ is the excitation with a upper bound $\phi_{up}(t) \geq \|\phi(t)\|$; U(t) corresponds to the actuator forces (generated via active a tendon system or an active mass damper, for example).

Thus

$$\forall R'_j, R'_k \in \mathbb{R}', d\left(R'_j, \mu_q\right) = d\left(R'_k, \mu_q\right) \tag{17}$$

where

$$d\left(R', \mu_q\right) = \sqrt{\textstyle\sum_{i=1}^{N} (\mathrm{rep}(A'_i) - \mu_{q,i})^2}, R' \in \mathbb{R}' \tag{18}$$

To generate an R^*, a weighted aggregation method is employed that calculates the contribution of every candidate rule in the selected cluster with respect to the cluster centroid u_q.This process is similar to the construction of intermediate rules in T-FRI, where a matrix $w_{ij}$of the rank

$C_q \times (N+1)$ is involved. It reflects the weighting of the antecedent A'_{ij} of an interpolated rule $R'_i \in C_q$ in relation to the jth antecedent A^*_j of R^* such that

$$w_{i,j} = \frac{1}{d(A'_{i,j}, \mu_{q,j})}, i \in \{1, \ldots, |C_q|\}, j \in \{1, \ldots, N\} \quad (19)$$

and similarly, that of B'_i of the interpolated rule to B^*

$$w_{i,N+1} = \frac{1}{d(B'_i, \mu_{q,N+1})} \quad (20)$$

The weights are then normalized, resulting in

$$w'_{i,j} = \frac{w_{i,j}}{\sum_{i=1}^{|C_q|} w_{i,j}} \quad (21)$$

With the resultant calculated weights, a new rule R^* is thus, dynamically constructed, such that

$$A^*_j = \sum_{i=1}^{|C_q|} w'_{i,j} A'_{i,j}, j \in \{1, \ldots, N\}, B^* = \sum_{i=1}^{|C_q|} w'_{i,N+1} B'_i \quad (22)$$

An LDI system can be described in the state-space representation (see Hu 2008 and Liu and Li 2010) as follows

$$\dot{Y}(t) = A(a(t))Y(t), \quad A(a(t)) = \sum_{i=1}^{r} h_i(a(t))\bar{A}_i \quad (23)$$

According to the interpolation method, we can obtain

$$\dot{X}(t) = \sum_{\Omega^\sigma} h_{\Omega^\sigma}(t) E_{\Omega^\sigma} \Lambda(t) \quad (24)$$

Finally, based on Eq. (23), the dynamics of the NN model can be rewritten as the following LDI state-space representation

$$\dot{X}(t) = \sum_{i=1}^{r} h_i(t)\bar{E}_i \Lambda(t) \quad (25)$$

Based on the above modeling schemes, the ocean structural system can be approximated as the T-S fuzzy model, which combines the flexibility of fuzzy logic theory and the rigorous mathematical analysis tools of a linear system theory into a unified framework. To ensure the stability of the ocean structure system, the T-S fuzzy model and the stability analysis are recalled. First, the ith rule of the T-S fuzzy model, representing the structural system, can be represented as follows

$$\text{Rule i: IF } x_1(t) \text{ is } M_{i1} \text{ and} \cdots \text{and } x_p(t) \text{ is } M_{ip} \quad (26)$$

$$\text{THEN } \dot{X}(t) = A_i X(t) + \bar{A}_i X(t-\tau) + E_i \phi(t) \quad (27)$$

Through using the fuzzy inference method with a singleton fuzzifier, product inference, and center average defuzzifier, the dynamic fuzzy model (36) can be expressed as follows

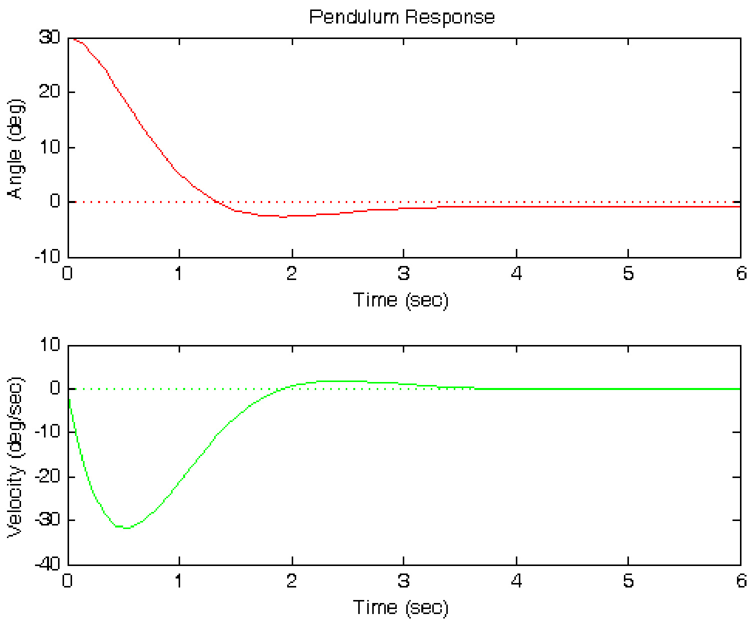

Fig. 1 The controlled system response by the designed controller

$$\dot{X}(t) = \frac{\sum_{i=1}^{r} w_i(t)[A_i X(t) + \bar{A}_i X(t-\tau) + E_i \phi(t)]}{\sum_{i=1}^{r} w_i(t)} \\ = \sum_{i=1}^{r} h_i(t)(A_i X(t) + \bar{A}_i X(t-\tau) + E_i \phi(t) \tag{28}$$

Theorem 1:

The augmented system is asymptotically stable in the large if there exists a common positive definite matrix $\tilde{P}$, the controller gains and observer gains, can be found to satisfy the following matrix inequalities

$$\left(\frac{\tilde{A}_{ij}(\alpha_m, \beta_m) + \tilde{A}_{ji}(\alpha_m, \beta_m)}{2} \right)^T \tilde{P} + \tilde{P} \left(\frac{\tilde{A}_{ij}(\alpha_m, \beta_m) + \tilde{A}_{ji}(\alpha_m, \beta_m)}{2} \right) < 0 \quad , \quad i < j \le r \tag{29}$$

4. The experiment design and the simulation result

The ocean structure system is able to be modeled from the dynamics

$$\frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -9 & -6 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 9r \end{bmatrix} \tag{30}$$

where x_1 is the radius of the pendulum vertically, x_2 represents the rotation velocity, and r indicates the demand output angle. A set of NN based fuzzy rules is employed to describe the temporary state of the nonlinear system. Similar operations can be found in previous studies (see Liu and Lin (2012, 2012a, 2013)). By combining the whole set of fuzzy rules, the approximation of the nonlinear system is completed. Thus, the fuzzy model approximated inverted pendulum nonlinear system can be described as follows:

A large population size provides a larger chance for the algorithm to find the near best solutions. However, a larger population size requires more memory resource and computation power. Hence, we set the population size to be 16 in the experiment.

Fig. 1 gives the simulation result controlled by the designed controller. On the other hand, the controller maintains the system to be held in the stable state.

5. Conclusions

This paper has presented a D-FRI approach for designing a dynamic rule-based fuzzy system and its application to network security analysis, building an intelligent dynamic IDS. D-FRI is used to select, combine, and promote informative, frequently used interpolated rules into an existing sparse rule base. Systematic experimental results have shown that D-FRI can achieve higher accuracy and robustness than those achievable by the use of conventional FRI.

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