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VOLUME I

Session 1 - Systems Engineering and Intelligent Systems

Session 2 - Advances in Control Theory and Control Engineering

Session 3 - Optimisation and Management of Complex Systems and Networked Systems

Session 4 - Intelligent Vehicles and Mobile Systems

Session 5 - Robotics and Motion Systems

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Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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2 Advances in Control Theory and Control Engineering

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Y. Gu / H. Su / J. Chu

An Approach for Transforming Nonlinear System Modeled by the Feedforward Neural Networks to Discrete Uncertain Linear System

ABSTRACT

In this paper, an approach for transforming a state-space or input-output representation nonlinear system modeled by feedforward NN to a discrete uncertain linear system is presented. First, The dynamics of the feedforward NN model are represented by linear difference inclusions (LDI's). Then, the LDI's are interpreted as discrete linear system with norm-bounded or polytopic time-varying uncertainties. Finally, we use some simulation results of a typical continuous stirred tank reactor (CSTR) to elaborate on the details of the above approach.

1. Introduction

Nonlinear system modeling and control is still an open problem now. Though nonlinear system modeling based on Neural Networks (NN) has made a great progress in recent years, the nonlinear controller synthesis for nonlinear system modeled by NN is still hard to be realized online due to the heavy computational burden and the difficulty in convergence. As a result, the most practical strategies recently are to linearize the involved NN model in the model based controller synthesis. In most cases, the uncertainties caused by linearization could not be neglected. Otherwise, the stability and performance characteristics of the nonlinear control system are not easy to be assessed. In the last few years, the research on robust stability and performance of linear systems with norm-bounded or polytopic uncertainties have achieved a lot[1]. So we want to build a bridge between the NN model and the uncertain linear system to integrate the nonlinear system control with NN into robust control[2],[3]. In this paper, a bridge between the feedforward NN and linear systems with norm-bounded or polytopic uncertainties is proposed.

2. Preliminaries

Usually, discrete nonlinear system could be described as state-space form or input-output form:

State-space form:

$$\begin{aligned} x(k) &= f[x(k-1), u(k-1)] \\ y(k) &= Cx(k) \end{aligned} \tag{2.1}$$

Input-output form:

$$y(k) = g[y(k-1), \cdots, y(k-n), u(k-1), \cdots, u(k-n)] \tag{2.2}$$

where f and g are nonlinear functions. f and g could be modeled by the Feedforward Neural Networks(FNN), which is sufficient to uniformly approximate arbitrary nonlinear mapping.

And, we describe some specific families of LDI's that we often encounter in robust control study:

Norm-bounded LDI's:

$$\begin{aligned} x(k+1) &= (A_0 + \Delta A)x(k) + (B_0 + \Delta B)u(k) \\ y(k) &= Cx(k) \end{aligned} \tag{2.3}$$

$$[\Delta A \quad \Delta B] = DF(k)[E_1 \quad E_2] \tag{2.4}$$

where $\Delta A \in R^{n\times n}$ and $\Delta B \in R^{n\times m}$ represent time-varying parameter uncertainties in the system model. $D \in R^{n\times r}$, $E_1 \in R^{l\times n}$ and $E_2 \in R^{l\times m}$ are known real constant matrices. $F(k)$ is an unknown time varying matrix, satisfying

$$\mathrm{N} = \{F(k) \in R^{r\times l} : F^T(\mathrm{k})F(k) \le I\} \tag{2.5}$$

Polytopic LDI's:

$$\begin{aligned} x(k+1) &= A(k)x(k) + B(k)u(k) \\ y(k) &= Cx(k) \\ [A(k) \quad B(k)] &\in \Omega \end{aligned} \tag{2.6}$$

where Ω is polytope, $\Omega = Co\{[A_1 \; B_1], [A_2 \; B_2], ..., [A_L \; B_L]\}$ where Co devotes to the convex hull.

According to a simple extension from [1], there are two corollaries as the following:

Corollary 2.1 State-space form（2.1）could be described as the uncertain linear system as follows:

$$\begin{aligned} \bar{x}(k) &= A(k)\bar{x}(k-1) + B(k)\bar{u}(k-1) \\ y(k) &= Cx(k) \end{aligned} \tag{2.7}$$

$$[A(k) \quad B(k)] \in Co\left[\frac{\partial f}{\partial x(k-1)}, \frac{\partial f}{\partial u(k-1)}\right]. \tag{2.8}$$

where, $\bar{x}(k) = x(k) - \tilde{x}(k)$, $\bar{u}(k) = u(k) - \tilde{u}(k)$. $[\tilde{x}(k) \quad \tilde{u}(k)]^T$ could be a known equilibrium trajectory.

Corollary 2.2 For input-output form（2.2）, denote

$$p(k) = [y(k-1), \cdots, y(k-n), u(k-1), \cdots, u(k-n)].$$

then（2.2）could be described as the uncertain linear system as follows:

$$\bar{y}(k)=H(k)\bar{p}^T(k) \tag{2.9}$$

$$H(k)\in Co\left[\frac{\partial g}{\partial y(k-1)},\cdots,\frac{\partial g}{\partial y(k-n)},\frac{\partial g}{\partial u(k-1)},\cdots,\frac{\partial g}{\partial u(k-n)}\right] \tag{2.10}$$

where $\bar{y}(k)=y(k)-\tilde{y}(k)$, $\bar{p}(k)=p(k)-\tilde{p}(k)$. $[\tilde{y}(k)\quad \tilde{p}(k)]^T$ could be a known equilibrium trajectory.

Since most robust control theory focus on state-space model, we now consider the state-sapce observer realization of (2.9):

$$\begin{aligned}x(k+1)&=A(k)x(k)+B(k)\bar{u}(k)\\ \bar{y}(k)&=Cx(k)\end{aligned} \tag{2.11}$$

$$A(k)=\begin{bmatrix}0 & \cdots & 0 & A_n(k)\\ I & \cdots & 0 & A_{n-1}(k)\\ \vdots & \ddots & \vdots & \vdots\\ 0 & \cdots & I & A_1(k)\end{bmatrix}\qquad B(k)=\begin{bmatrix}B_n(k)\\ B_{n-1}(k)\\ \vdots\\ B_1(k)\end{bmatrix} \tag{2.12}$$

$$C=[0\quad 0\quad \cdots\quad I]$$

where, $A_i(k)=\dfrac{\partial g}{\partial y(k-i)},\quad B_i(k)=\dfrac{\partial g}{\partial u(k-i)}$

3. Transforming FNN to Discrete Uncertain Linear System

In this section, we discuss the problem of the formulation for transforming weights of FNN to parameter matrices of norm-bounded uncertain linear system and vertexes of polytopic uncertain linear system. The active function in the neuron of FNN is Tansig function. The output value of Tansig function is bounded in (-1,1).

3.1 Norm-bounded Uncertainties

3.1.1 System(2.1) modeled by a single hidden layer FNN

Consider the nonlinear function f in system(2.1) , which is modeled by a single hidden layer FNN. The Jacobian matrix of the FNN is as the following:

$$J=\left[\frac{\partial f}{\partial x(k-1)}\quad \frac{\partial f}{\partial u(k-1)}\right]=W_2\times diag(1-a.\times a)\times W_1 \tag{3.1}$$

where $a=f(W_1\times p+B_1)$. is output vector of the hidden layer,$.\times$represent the array multiplication. $diag(a_{s\times 1})$ denotes a square diagonal matrix with $a(1),\ldots,a(s)$ on the main diagonal. W_1 is the matrix of connecting weights between the input-layer and the hidden-layer, W_2 is that between the hidden-layer and the output-layer.

According to Corollary 2.1, system (2.1) could be transformed to (2.7). Hence,

$$[A(k)\quad B(k)]=W_2\times diag(1-a.\times a)\times W_1 \tag{3.2}$$

Then system (2.1) could be further tranformed to (2.3). The nominal model is the linearization model on an equilibrium.

$$[A_0 \quad B_0] = W_2 \times diag(1 - a_0 . \times a_0) \times W_1 \tag{3.3}$$

The uncertainties are as the following:

$$[\Delta A(k) \quad \Delta B(k)] = W_2 \times diag(a_0 . \times a_0 - a . \times a) \times W_1 \tag{3.4}$$

$$D = W_2,\ [E_1 \quad E_2] = W_1,\ F(k) = diag(a_0 . \times a_0 - a . \times a) \tag{3.5}$$

And the value of each element in the diagonal matrix $F(k)$ is in $(-1, 1)$, so obviously the norm-bounded condition (2.5) is satisfied.

3.1.2 System(2.2) modeled by a single hidden layer FNN

Consider the nonlinear function g in system(2.2), which is modeled by a single hidden layer FNN with the input vector $p(k) = [y(k-n), \cdots, y(k-1), u(k-n), \cdots, u(k-1)]$.

According to Corollary 2.2, system (2.2) could be transformed to (2.9), and further transformed to state-space model (2.11), (2.12) . Then we have,

$$[A_n(k), \cdots, A_1(k), B_n(k), \cdots, B_1(k)] = W_2 \times diag(1 - a . \times a) \times W_1 \tag{3.6}$$

We get W_1 partitioned with appropriate dimensions, and substituted the partitioned W_1 in (2.12) to get:

$$A(k) = \begin{bmatrix} 0 & \cdots & 0 & \\ I & \cdots & 0 & W_{1A}^T \times diag(1 - a . \times a) \times W_2^T \\ \vdots & \ddots & \vdots & \\ 0 & \cdots & I & \end{bmatrix} \tag{3.7}$$

$$B(k) = W_{1B}^T \times diag(1 - a . \times a) \times W_2^T \tag{3.8}$$

The nominal model could be set to the linearization model on one equilibrium. Then (3.7),(3.8) could be transformed to(2.3),(2.4):

$$A_0 = \begin{bmatrix} 0 & \cdots & 0 & \\ I & \cdots & 0 & W_{1A}^T \times diag(1 - a^0 . \times a^0) \times W_2^T \\ \vdots & \ddots & \vdots & \\ 0 & \cdots & I & \end{bmatrix} \tag{3.9}$$

$$B_0 = W_{1B}^T \times diag(1 - a^0 . \times a^0) \times W_2^T \tag{3.10}$$

$$[\Delta A(k) \quad \Delta B(k)] = DF(k)[E_1 \quad E_2] \tag{3.11}$$

where $F(k) = \begin{bmatrix} F_A(k) & \\ & F_B(k) \end{bmatrix}$, $D = [D_A \quad D_B]$, $E_1 = \begin{bmatrix} E_A \\ 0 \end{bmatrix}$, $E_2 = \begin{bmatrix} 0 \\ E_B \end{bmatrix}$ (3.12)

$$D_A = W_{1A}^T,\ D_B = W_{1B}^T,\ F_A(k) = F_B(k) = diag(a^0 . \times a^0 - a . \times a), \tag{3.13}$$

$$E_A = \begin{bmatrix} 0 & \cdots & 0 & \\ 0 & \cdots & 0 & W_2^T \\ \vdots & \ddots & \vdots & \\ 0 & \cdots & 0 & \end{bmatrix},\ E_B = W_2^T \tag{3.14}$$

Since the output value of Tansig function in hidden neuron is in $(-1,1)$, so obviously $F^T(k)F(k) < I$ is satisfied.

3.2 Polytopic Uncertainties

The above norm-bounded LDI's are all diagonal norm-bounded LDI with an uncertain diagonal matrix $F(k)$. And the diagonal norm-bounded uncertainties could be described as polytopic uncertainties[1]. The vetexes are the linear nominal models when the elements of $F(k)$ take their extreme value. The number of the vetexes is obtained according to permutation and combination. There are two corollaries as the following:

Corollary 3.1 The nonlinear system modeled by a single hidden-layer feedforward NN could be represented by a polytopic uncertain system with 2^s vertexes at most, where s is the number of nodes of the hidden-layer.

Corollary 3.2 The nonlinear system modeled by a double hidden-layers feedforward NN could be represented by a polytopic uncertain system with $2^{s+t} - 2^s - 2^t + 2$ vertexes at most, where s is the number of nodes of the first hidden-layer, and t is that of the second one.

4. An Example

Let's consider a typical CSTR process[4] now. The single hidden layer FNN for modelling the CSTR is first identified by the input-output data. The topology structure of the FNN is 3-4-2.

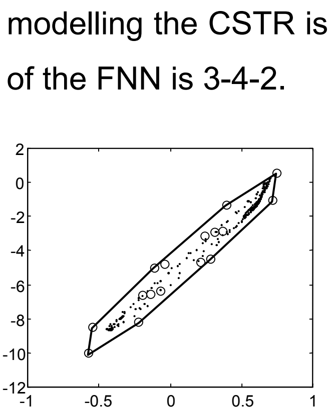

Fig. 4.1 a_{11} and a_{21} of $A(k)$

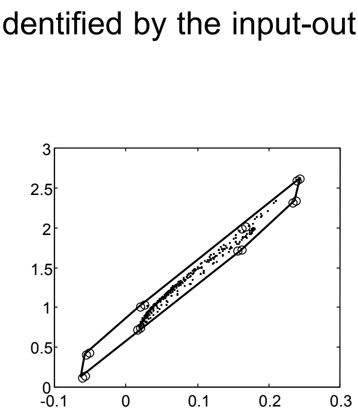

Fig.4.2 a_{12} and a_{22} of $A(k)$

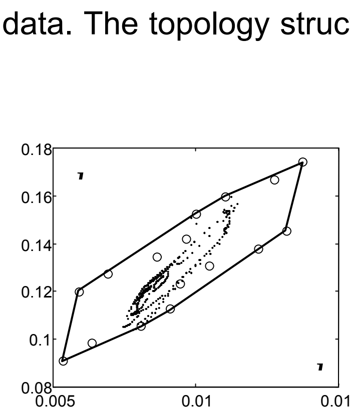

Fig. 4.3 b_1 and b_2 of $B(k)$

Then, the FNN could be transformed to an uncertain linear system (3.2)~(3.5). where $A(k) \in R^{2\times2}$, $B(k) \in R^{2\times1}$, and the equilibrium is selected as the middle unstable equilibrium(0.447, 2.751, 0). We group every two elements of the matrices $A(k), B(k)$

and project the uncertainties of the elements to the Fig. 4.1~4.3. The dots in the figures are obtained by the equations (3.3) on every input-output sampling data. According to Corollary 3.1, the polytopic uncertain system has $2^4 = 16$ vetexes at most. The circles in the figures are the potential vetexes.

5. Conclusion

Based on the above work, the robust control strategies could be applied to the nonlinear controller synthesis incorporating the feedforward NN model. And, the robust stability and robust performance of the corresponding nonlinear control system is convenient to be assessed. Then a systematic procedure for nonliear process control could be provided with our contribution. We could firstly model the real process with the feedforward NN model just based on the input and output data. Secondly, the resulted NN would be transformed to uncertain linear system with the approch in this paper. Thirdly, many robust control strategies could be attempted to analyse and synthesis the uncertain linear system. Finally, the derived controller is applied to the real process with some anticipative stability and performance. It is noted that uncertain linear system is always conservative compared with the feedforward NN. The conservatism has direct impact on the successful implementation of this procedure. Then how to reduce the conservatism in this procedure will be further studied in the future.

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