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A neural network-based robust unknown input observer design: Application to wind turbine. [1]

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Abstract: The paper deals with the problem of robust unknown input observer design for the neural-network based models of non-linear discrete-time systems. Authors review the recent development in the area of robust observers for non-linear discrete-time systems and proposes less restrictive procedure for design the $\mathcal{H}_\infty$ observer. The approach guaranties simultaneously the predefined disturbance attenuation level (with respect to state estimation error) and convergence of the observer. The main advantage of the design procedure is its simplicity. The paper presents an unknown input observer design that reduced to a set of linear matrix inequalities. The final part of the paper presents an illustrative example concerning wind turbine.

Keywords: Observer, Fault Diagnosis, Unknown Inputs, Robustness, System Identification, Takagi-Sugeno systems, Artificial Neural Networks, Sector Non-linearities.

1. INTRODUCTION

The paper tackles with the problem of design Unknown Input Observer for simultaneous state and fault estimation of non-linear discrete-time systems described by Takagi-Sugeno (TS) models Takagi and Sugeno [1985]. The paper revisits recent results in this area Chadli and Karimi [2013], and provides less restrictive design procedure for the design of a robust UIO. The general UIO strategy and the $\mathcal{H}_\infty$ framework are used to design a robust fault estimation scheme. The resulting design procedure guarantees that a prescribed disturbance attenuation level is achieved with respect to the state estimation error, while guaranteeing the convergence of the observer with a possibly large decay rate of the state estimation error. The main advantage of the proposed approach boils down to its simplicity, i.e., it reduces to solving a set of Linear Matrix Inequalities (LMIs), which can be efficiently solved with modern computational packages. The efficient Fault-Tolerant Control Witczak and Witczak [2013], Witczak et al. [2014] is impossible without information about the fault Cardenas et al. [2013], Evangelista et al. [2013], Witczak et al. [2013]. This is the reason why fault diagnosis emerges on the first plan. During the last decade, several mature methods both for linear and non-linear systems were developed Iserman [2011], Korbicz et al. [2004], Mrugalski [2014]. Unfortunately, efficient fault estimation, especially for non-linear systems, are still needed. As authors shows in the paper fault estimation can be also perceived as the estimation of an unknown input and has received considerable attention in the literature. Among numerous approaches, some deserve a special attention, e.g.: augmenting the state vector adding an unknown input Witczak [2014], minimum variance input and state estimator Gillijns and De Moor [2007], adaptive estimation Zhang and Prisini [2010], sliding mode high-gain observers Veluvolu et al. [2011], and last but not least, an $\mathcal{H}_\infty$ approaches Nobrega et al. [2008].

However the approach of designing UIO for non-linear systems described by TS model would not be complete without providing an effective way for system identification. The FTC and FDI Witczak [2014] methods for linear systems are widely developed Mrugalski [2013], Mrugalski and Witczak [2012], Inseok et al. [2010] and perform better that their non-linear counterparts Varga and Ossmann [2014], Silva and Moulin [2000], Chen et al. [2011], Inseok et al. [2010], thus a need for linearization methods manifests. Widely used fuzzy representations as Takagi-Sugeno model appears to be an effective answer to an exhibited demand Panchariya et al. [2004], Johansen et al. [2000], Abonyi and Babuska [2000], Li and Pengfei [2013], Alexiev and Georgieva [2004]. Therefore for completeness of the paper authors present a novel identification method, which boils down to four steps:

- Train neural network to mimic non-linear system
- Obtain weights of the neurons

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- Build constrained set representation via Sector Nonlinearity concept
- Find the multi-variable membership function

The paper is organized as follows. Section 2 provides a background on the TS systems as well as Sector Nonlinearity concept along with its usage for fuzzy modeling and recent developments in the associated area of the UIO design. Section 4 presents a way for the system identification along with the membership function. Subsequently, section 5 provides a novel UIO design procedure, which relaxes restrictive conditions of the competitive approaches. It also depicts a design procedure that can be used for fault estimation, which is based on the state estimates provided by the developed UIO. Section 6 delivers a complete example for the proposed robust UIO of the identified system. The final part of the paper concerns the concluding remarks.

2. PRELIMINARIES

2.1 Takagi-Sugeno discrete-time systems

A non-linear dynamic system can be described in a relatively simple way by a Takagi-Sugeno model, by using series of locally linearised models from the non-linear system. According to this model, a discrete-time non-linear dynamic systems can be described by linear models representing the local system behaviour around some operating points. Thus, a fuzzy fusion of all linear model outputs describes the global system behaviour. The Takagi-Sugeno model is described by fuzzy IF-THEN rules. It has a rule base of M rules, each having p antecedents, where ith rule is expressed as

$$R^{(i)} : \text{IF } s_k^{(1)} \text{ is } F_1^{(i)} \text{ and } \ldots s_k^{(p)} \text{ is } F_p^{(i)}, \text{ THEN}$$

$$\boldsymbol{x}_{k+1} = \boldsymbol{A}^{(i)}\boldsymbol{x}_k + \boldsymbol{B}^{(i)}\boldsymbol{u}_k + \boldsymbol{B}^{(i)}\boldsymbol{f}_k + \boldsymbol{W}_1^{(i)}\boldsymbol{w}_k, \quad (1)$$

$$\boldsymbol{y}_k = \boldsymbol{C}\boldsymbol{x}_k + \boldsymbol{W}_2^{(i)}\boldsymbol{w}_k, \quad (2)$$

where $\boldsymbol{x}_k \in \mathbb{R}^n$ stands for the state, $\boldsymbol{y}_k \in \mathbb{R}^m$ is the output, and $\boldsymbol{u}_k \in \mathbb{R}^r$ denotes the nominal control input, $\boldsymbol{f}_k \in \mathbb{R}^r$ is the actuator fault, $i = 1, \ldots, M$, F_j^i $(j = 1, \ldots, p)$ are fuzzy sets and $\boldsymbol{s}_k = [s_k^1, s_k^2, \ldots, s_k^p]^T$ is a known vector of premise variables Korbicz et al. [2004], Takagi and Sugeno [1985], and $\boldsymbol{w}_k \in \mathbb{R}^n$ is a an exogenous disturbance vector. The TS models considered in Chadli and Karimi [2013] are:

$$\boldsymbol{x}_{k+1} = \sum_{i=1}^{M} h_i(\boldsymbol{s}_k)[\boldsymbol{A}^{(i)}\boldsymbol{x}_k + \boldsymbol{B}^{(i)}\boldsymbol{u}_k + \boldsymbol{B}^{(i)}\boldsymbol{f}_k + \boldsymbol{W}_1^{(i)}\boldsymbol{w}_k], \quad (3)$$

$$\boldsymbol{y}_k = \boldsymbol{C}\boldsymbol{x}_k + \boldsymbol{W}_2\boldsymbol{w}_k, \quad (4)$$

where $h_i(\boldsymbol{s}_k)$ are normalized rule firing strengths.

2.2 Unknown Input Observer design

The unknown input observer associated with (3)-(4) can be defined as

$$\boldsymbol{z}_{k+1} = \sum_{i=1}^{M} h_i(\boldsymbol{s}_k)[\boldsymbol{N}^{(i)}\boldsymbol{z}_k + \boldsymbol{G}^{(i)}\boldsymbol{u}_k + \boldsymbol{L}^{(i)}\boldsymbol{y}_k], \quad (5)$$

$$\hat{\boldsymbol{x}}_k = \boldsymbol{z}_k - \boldsymbol{E}\boldsymbol{y}_k. \quad (6)$$

Remark 1. The fault $\boldsymbol{f}_k$ along with its distribution matrices $\boldsymbol{B}^{(i)}$, $i = 1, \ldots, M$ can be perceived as an unknown input.

Let us define the state estimation error $\boldsymbol{e}_k = \boldsymbol{x}_k - \hat{\boldsymbol{x}}_k$, which for (3)–(4) and (5)–(6) obeys:

$$\begin{aligned}\boldsymbol{e}_{k+1} = \sum_{i=1}^{M} h_i(\boldsymbol{s}_k) \Big[& \boldsymbol{N}^{(i)}\boldsymbol{e}_k + (\boldsymbol{T}\boldsymbol{A}^{(i)} - \boldsymbol{K}^{(i)}\boldsymbol{C} - \boldsymbol{N}^{(i)})\boldsymbol{x}_k + \\ & + (\boldsymbol{T}\boldsymbol{B}^{(i)} - \boldsymbol{G}^{(i)})\boldsymbol{u}_k + \boldsymbol{T}\boldsymbol{B}^{(i)}\boldsymbol{f}_k + \\ & + (\boldsymbol{T}\boldsymbol{W}_1^{(i)} - \boldsymbol{K}^{(i)}\boldsymbol{W}_2)\boldsymbol{w}_k + \boldsymbol{E}\boldsymbol{W}_2\boldsymbol{w}_{k+1}\Big].\end{aligned} \quad (7)$$

with

$$\boldsymbol{T} = \boldsymbol{I} + \boldsymbol{E}\boldsymbol{C}, \quad \boldsymbol{K}^{(i)} = \boldsymbol{N}^{(i)}\boldsymbol{E} + \boldsymbol{L}^{(i)}, \quad (8)$$

which under

$$\boldsymbol{N}^{(i)} = \boldsymbol{T}\boldsymbol{A}^{(i)} - \boldsymbol{K}^{(i)}\boldsymbol{C}, \quad (9)$$

$$\boldsymbol{T}\boldsymbol{B}^{(i)} - \boldsymbol{G}^{(i)} = \boldsymbol{0}, \quad (10)$$

$$\boldsymbol{T}\boldsymbol{B}^{(i)} = \boldsymbol{0}, \quad (11)$$

$$\boldsymbol{E}\boldsymbol{W}_2 = \boldsymbol{0}, \quad (12)$$

$$\boldsymbol{T}\boldsymbol{W}_1^{(i)} - \boldsymbol{K}^{(i)}\boldsymbol{W}_2 = \boldsymbol{0}, \quad (13)$$

boils down to

$$\boldsymbol{e}_{k+1} = \sum_{i=1}^{M} h_i(\boldsymbol{s}_k)\boldsymbol{N}^{(i)}\boldsymbol{e}_k. \quad (14)$$

2.3 Sector non-linearity and fuzzy membership

Even though idea of sector non-linearity is relatively simple, for completness of the proposed aproach let us recall the phenonena. The function $f : \Re \to \Re$

$$y = f(x) \quad (15)$$

is said to be in $[l, r]$ iff $\forall x \in \Re, y = f(x)$ lies between lx and rx. This can be expressed as an quadratic inequality

$$(f(x) - rx)(f(x) - lx) \leq 0 \quad \forall x \in \Re \quad (16)$$

Following work of Ohtake et al. [2001] for the single variable function, like (15) fuzzy membership function are constructed as

$$h_r(x) = \frac{f(x) - lx}{(r - l)x} \quad h_l(x) = \frac{rx - f(x)}{(r - l)x} \quad (17)$$

with $h_l(x) + h_r(x) = 1$ and $h_l(x), h_r(x) \geq 0$

3. NEURAL NETWORK STATE-SPACE MODELING

Let us consider a discret-time non-linear system

$$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \boldsymbol{u}_k) \quad (18)$$

where $\boldsymbol{x}_k \in \Re^n$ is the state vector and $\boldsymbol{u}_k \in \Re^r$ stands for system input. Function $f : \Re^n \times \Re^r \to \Re^n$ is an unknown continous mapping of the states and inputs. Using Neural Network theory, i.e(Lu and Basar [1998]) the (18) can be approximated with a desired accuracy by a Multi Layer Perceptron (MLP) with a finite, large enough number p of neurons in a single hidden layer. Therefore

$$f(\tilde{\boldsymbol{x}}_k, \tilde{\boldsymbol{u}}_k) = \boldsymbol{W}_0\sigma(\boldsymbol{W}_x\tilde{\boldsymbol{x}}_k + \boldsymbol{W}_u\tilde{\boldsymbol{u}}_k + \tilde{\boldsymbol{W}}_b) + \epsilon_x \quad (19)$$

where $\boldsymbol{W}_0 \in \Re^{n\times p}$, $\boldsymbol{W}_x \in \Re^{p\times n}$ and $\boldsymbol{W}_u \in \Re^{p\times r}$ are the output and hidden layer weights respectively, $\sigma(\bullet)$ is any activation (odd) function, e.g. hyperbolic tangent (Witczak [2014] proves the choice of function is irrelevant).