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Multimodel robust observer for an uncertain fish population model

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ABSTRACT

In this paper, a new method is proposed to design an observer for a nonlinear and uncertain system describing a continuous stage structured model of a harvested fish population. The aim is to get an estimation of the biomass of fishes by stage class. In the studied model the fishing effort is considered as a control term, the stage classes as states and the quantity of captured fish as a measured output. A Takagi–Sugeno multimodel first represents the uncertain non-linear model. Next, we develop a technique for designing a multimodel observer corresponding to this system, which attenuates the effect of modelling uncertainties and measurement noise on the state estimation. The design conditions are given in linear matrix inequalities (LMIs) terms that can be solved efficiently using existing numerical tools. The validity of the proposed method is illustrated by the simulation results.

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1. Introduction

Fisheries are a valuable resource that should be managed in a way that delivers the highest net positive outcomes to society, where the environment and society are fully taken into account [21]. Well-managed fisheries benefit society in a variety of ways: sustaining food supply, livelihoods, and coastal communities while also permitting a healthy environment [7]. A key condition critical to build effective fisheries management regimes is the understanding of the status of fisheries. Therefore, the ability to conduct stock assessments and make accurate estimates of fish abundance is the basis of both ecological and environmental effects studies. The assessment of fish populations by direct observation should be based ideally on synoptic data that are precise (no measurement error), as exhaustive as possible (spatially complete), and global (cover the entire population area) [18]. However, it is not possible or at least difficult and expansive to fulfil these requirements in practice. Consequently, the question arises whether from the observation of certain indicators of the considered system; the whole state of the population can be recovered or at least estimated.

In this sense, we consider in this work an uncertain model that describes the dynamic of a structured fish population and subject to the fishing action. The individuals in the population are partitioned into classes, or stages, according to age, length or weight. Uncertainty includes scientific uncertainties related to resource dynamics or assessments, and external disturbances such as noises or faults. We show that a tool from control theory called "an observer" can be helpful to address the resource stock estimation in the field of fisheries management. In control theory, an observer can be viewed as a dynamic system that estimates the immeasurable variables or model parameters of a plant using its input–output measurements. Thus the problem of observer design in fisheries is how to get an estimate for the state of the biomass from the knowledge of the fishing effort, total caught and system model.

The question of stock estimation has been addressed in EL Mazoudi et al. [8,9], Ngom et al. [4], Guiro et al. [2] and Ouahbi [3]. EL Mazoudi et al. [9] proposed the high gain observer technique for the continuous age-structured fish population model without uncertainties in order to get an estimation of the biomass of fishes by age class. A similar technique was used by EL Mazoudi et al. [8] for the uncertain continuous age-structured model. Ngom et al. [4] constructed an observer for a stage structured discrete-time fishery model that exhibits an unknown recruitment function. Guiro et al. [2] considered a stage structured continuous model and assumed that only the last class (mature individuals) is harvested. Ouahbi [3] constructed an observer that gives an estimate of the state of the discrete time model and which is independent of the choice of stock recruitment function.

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Improving the performance of observers has been extensively studied in many papers (see e.g., [5,11,12], and the references therein) to develop observers that are robust against uncertainties of modelling and external disturbances such as noises or faults. In this context, substantial research efforts have been devoted to Takagi–Sugeno (T–S) [16] fuzzy systems due to flexibility of their structure to incorporate linguistic information (expert knowledge) with numerical information (sensors and actuators measurements), as well as their functional efficiency as universal approximators [6,10] capable of adequately treating uncertainties, parametric variations and nonlinearity of the system to be controlled. The basic idea for the approach is to decompose the model of a nonlinear system into a set of linear subsystems with associated nonlinear weighting functions. They can represent exactly a nonlinear model [11]. From this exact model, a fuzzy state observer may be designed based on the linear subsystems [12].

To the best of our knowledge, the problem of estimating uncertain exploited fish population systems via multimodel observer and using T–S fuzzy model has not been studied in the literature. In this work a T–S robust observer is proposed and applied to an uncertain continuous nonlinear fish population system. The robust observer gains are calculated using linear matrix inequalities (LMIs) [20].

The rest of this paper is organized as follows. In Section 2, we present an overview of dynamic T–S systems and the main results to design the multimodel robust observer are given under LMI formulation. Section 3 deals with the description of the uncertain continuous stage structured model, which is transformed to a T–S fuzzy model. In Section 4, the procedure to design the robust observer estimating the stage classes' biomass is applied, and simulation results and comparisons with another method [1] are given to highlight the effectiveness of the design procedure.

2. Background

2.1. Model representation

A dynamic T–S fuzzy model is described by a set of fuzzy "IF … THEN" rules with fuzzy sets in the antecedents and dynamic linear time-invariant systems in the consequents. A generic T–S plant rule can be written as follows [11]:

Model Rule i :

IF $z_1(t)$ *is* M_{i1} *and* … *and* $z_p(t)$ *is* M_{ip},

THEN $\dot{x}(t) = A_i x(t) + B_i u(t)$

$\dot{y}(t) = C_i x(t)$

Here M_{ij} is the fuzzy set, $x(t) \in \boldsymbol{R}^n$ is the state vector, $u(t) \in \boldsymbol{R}^m$ is the input vector, $y(t) \in \boldsymbol{R}^q$ is the output vector, $A_i \in \boldsymbol{R}^{nxn}$, $B \in \boldsymbol{R}^{nxm}$, and $C \in \boldsymbol{R}^{qxn}$; $z_1(t),\dots z_p(t)$ are known premise variables that may be functions of the state variables, external disturbances, and/or time.

We will use $z(t)$ to denote the vector containing all the individual elements $z_1(t),\dots z_p(t)$, and r to denote the number of model rules.

Given a pair of ($x(t)$, $u(t)$), and using singleton fuzzifier, max-product inference and centre average defuzzifier, we can write the aggregated fuzzy model as:

$$\dot{x}(t) = \frac{\sum_{i=1}^{r} w_i\{z(t)\}\{A_i x(t) + B_i u(t)\}}{\sum_{i=1}^{r} w_i(z(t))} \tag{1}$$

where $z(t) = [z_1(t)\ z_2(t)\dots\ z_p(t)]$, and $w_i\{z(t)\} = \prod_{j=1}^{p} M_{ij}\{z_j(t)\}$.

The term $M_{ij}\{z_j(t)\}$ is called the membership function. It is the grade of membership of $z_j(t)$ in M_{ij}.

(1) can be written as follows:

$$\dot{x}(t) = \sum_{i=1}^{r} \mu_i\{z(t)\}\{A_i x(t) + B_i u(t)\}$$

where $\mu_i\{z(t)\} = w_i\{z(t)\}/\sum_{j=1}^{r} w_j\{z(t)\}$. $\mu_i\{z(t)\}$ is called the activation function.

Since $\sum_{i=1}^{r} w_i\{z(t)\} > 0$ and $w_i\{z(t)\} \geqslant 0, i = 1, 2, \dots, r$, we have: $\sum_{i=1}^{r} \mu_i\{z(t)\} = 1$ and $\mu_i\{z(t)\} \geqslant 0, i = 1, 2, \dots, r$, for all t.

The global output of T–S model is interpolated as follows:

$$y(t) = \sum_{i=1}^{r} \mu_i\{z(t)\} C_i x(t)$$

It should be pointed out that at a specific time, only a number s of local models is activated, depending on the structure of the activation functions μ_i (.).

In the next subsection, the design of the multimodel robust observer is presented, based on the results given by Ichalal et al. [5].

2.2. Robust fuzzy observer design

Let us consider the following uncertain multiple model with immeasurable decision variables:

$$\dot{x}(t) = \sum_{i=1}^{r} \mu_i\{z(t)\}\{(A_i + \Delta A_i)x(t) + (B_i + \Delta B_i)u(t)\} \tag{2a}$$

$$y = Cx + D\omega \tag{2b}$$

where $\omega(t)$ is a bounded measurement noise.

The matrices ΔA_i and ΔB_i, which may be time varying, represent the norm-bounded parameter uncertainties and can be written as [13]:

$$\begin{aligned} \Delta A_i(t) &= M_i^A \Sigma_A(t) N_i^A \\ \Delta B_i(t) &= M_i^B \Sigma_B(t) N_i^B \end{aligned}$$

where:

- $\Sigma_A(t)$ and $\Sigma_B(t)$ are real uncertain matrix functions with Lebesgue measurable elements and meet:
- $I \geqslant \Sigma_A^T(t)\Sigma_A(t)\ \forall t$, and $I \geqslant \Sigma_B^T(t)\Sigma_B(t)\ \forall t$, where I is the identity matrix.
- M_i^A, N_i^A, M_i^B, N_i^B are known real constant matrices of appropriate dimension that specify how the uncertain parameters in $\Sigma_A(t)$ and $\Sigma_B(t)$ enter the nominal matrices ΔA_i and ΔB_i, respectively.

Note that this structure of uncertainty parameters has been widely used in the problems of robust control and filtering of uncertain systems [15,24,19,14]. Several arguments in favour of using it can be found in Khargonekar et al. [17].

The system (2) can be represented as follows:

$$\dot{x}(t) = \sum_{i=1}^{r} \mu_i\{\hat{x}(t)\}\{(A_i + \Delta A_i)x(t) + (B_i + \Delta B_i)u(t) + v\}$$

$$y = Cx + D\omega$$

where $v = \sum_{i=1}^{r} [\mu_i\{x(t)\} - \mu_i\{\hat{x}(t)\}]\{(A_i + \Delta A_i)x(t) + (B_i + \Delta B_i)u(t)\}$.

The term $v(t)$ is considered as a perturbation. The proposed observer is defined by:

$$\hat{x}' = \sum_{i=1}^{r} \mu_i\{\hat{x}(t)\}[A_i\hat{x}(t) + B_i u(t) + G_i\{y(t) - \hat{y}(t)\}]$$

$$\hat{y}(t) = C\hat{x}(t)$$

where the G_i are to be calculated later.

Let us define the state estimation error:

$$e(t) = x(t) - \hat{x}(t)$$

Its dynamics are given by:

$$\dot{e}(t) = \sum_{i=1}^{r} \mu_i\{\hat{x}(t)\}\{(A_i - G_i C)e + \mathcal{M}_i\varpi\}$$

where $\mathcal{M}_i = [v^T \omega^T x^T u^T]^T$ and $\varpi = [I \ \ -G_i D\ \Delta A_i\ \Delta B_i]$.

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