Applied Soft Computing 17 (2014) 67–78

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Hybrid-fuzzy modeling and identification

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ARTICLE INFO

Article history:
Received 26 May 2012
Received in revised form
18 November 2013
Accepted 22 December 2013
Available online 8 January 2014

Keywords:
Fuzzy identification
Hybrid systems
Fuzzy clustering
Principal component analysis
Switching regression models

ABSTRACT

In this paper a class of hybrid-fuzzy models is presented, where binary membership functions are used to capture the hybrid behavior. We describe a hybrid-fuzzy identification methodology for non-linear hybrid systems with mixed continuous and discrete states that uses fuzzy clustering and principal component analysis. The method first determines the hybrid characteristic of the system inspired by an inverse form of the merge method for clusters, which makes it possible to identify the unknown switching points of a process based on just input–output (I/O) data. Next, using the detected switching points, a hard partition of the I/O space is obtained. Finally, TS fuzzy models are identified as submodels for each partition. Two illustrative examples, a hybrid-tank system and a traffic model for highways, are presented to show the benefits of the proposed approach.

1. Introduction and backgrounds

Hybrid systems represent a class of dynamical systems that contain continuous and discrete/integer variables. Different types of models can be used to represent hybrid systems [1,2], for example mixed logical dynamic (MLD) models, complementarity systems, piece-wise affine (PWA) models, max–min plus scaling systems, timed or hybrid Petri-nets, differential automata, switched systems, hybrid inclusions, and real-time temporal logics, among others. Each sub-class has its own advantages over the others. For example, control techniques have been developed for MLD hybrid models, stability criteria for PWA systems, and conditions of existence and uniqueness of solution trajectories for linear complementarity systems (see [3,4] and the references within).

For non-linear systems, a broad family of identification methodologies are available, for fuzzy, neural networks, neuro-fuzzy models [5–9]. However, few methodologies consider non-linear models with continuous and discrete variables, i.e. identification of hybrid systems. In general, the identification of hybrid systems requires to solve two issues: to classify the different modes of operation (discrete behavior) and to estimate the parameters for each mode. Assuming prior knowledge about the discrete modes is not the interest of this paper, because the identification of the model parameters for each mode can be performed straightforwardly using conventional identification techniques. In the literature, the identification methods for hybrid systems mainly focus on Piece-wise AutoRegressive eXogenous (PWARX) systems. In [10] an extensive comparison between some of those methods and their drawbacks is presented, and in [11] a recent and complete review of identification methods for hybrid systems (including among other topics like system description, state estimation, control, etc.) can be found. Next, some of those procedures are briefly described.

1.1. Identification methods for hybrid systems

Ferrari-Trecate et al. [12] propose a methodology for the identification of discrete-time hybrid systems in the PWA form, formulated as a discontinuous PWA map. The algorithm is based on clustering, linear identification, and pattern recognition techniques. An algebraic identification procedure to cope with the identification problem of Switched AutoRegressive eXogenous (SARX) systems was proposed by Ma and Vidal [13]. Multiple ARX models are encoded in a single polynomial expression that decouples the determination of parameters from the switching mechanism. The Bayesian procedure for the identification of Piece-wise AutoRegressive eXogenous (PWARX) systems proposed by Juloski et al. [14], exploits some prior knowledge about the discrete states and parameters of the submodels. The parameters of

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http://dx.doi.org/10.1016/j.asoc.2013.12.011

submodels are treated as random variables, and described through their probability density functions. A bounded-error procedure was proposed by Bemporad et al. [15] in order to identify PWARX systems. The main feature of the method is to ensure that the identification error is bounded for all data points. Nakada et al. [16] address the problem of identifying PWARX systems by using statistical clustering. The method consists of clustering the measured data, while estimating the boundary hyperplane and the parameters. Gegundez et al. [17] present an identification method for PWA systems based on fuzzy clustering and competitive learning. The method estimates the number of submodels of the system, the parameters corresponding to each submodel, and the regions in the regression space. Lauer et al. [18] propose a nonlinear hybrid system identification method based on kernel functions in order to estimate arbitrary nonlinearities without prior knowledge.

1.2. Fuzzy identification

Many advances in fuzzy systems identification and applications are available in the literature [19–24], including observers [25,26] and control methods [27,28]. Nefti et al. [29] present a method for merging fuzzy sets based on clustering in the parameter space. The fuzzy sets are replaced by the most compatible prototypical fuzzy set, which is determined from a inclusion-based clustering algorithm. Hadjili and Wertz [30] propose an identification method for Takagi–Sugeno (TS) models, incorporating the selection of optimal rules and input variables. The subtractive clustering algorithm, based on compactness and the separation of clusters, is performed in order to determine the number of rules. Roubos and Setnes [31] propose a complexity-reduction algorithm based on genetic-algorithm optimization procedures to find redundancy among the rules with a criterion based on maximum accuracy and maximum set similarity. In addition, Kim et al. [32] present a combined identification method, based on the TS and Sugeno–Yasukawa models. The approach implements fuzzy regression clustering for initial tuning of the parameters and a gradient-descent method to adjust them accurately. In Abonyi et al. [33] a modified Gath–Geva fuzzy clustering algorithm for the identification of TS models is proposed to directly obtain the parameters of the membership functions. A linear transformation of the input variables makes it possible to recover accurately the fuzzy partition of the antecedents. Li et al. [34] propose a new fuzzy c-regression model clustering algorithm where the clustering prototype in fuzzy space partition is a hyperplane. The new clustering algorithm is used in the identification of TS fuzzy model, obtaining good results in the identification of the premise parameters of the model.

1.3. Hybrid-fuzzy identification

For hybrid-fuzzy models, stability analysis and control designs have been proposed in the literature [35,36]. Regarding the identification of hybrid-fuzzy systems, although most of the developments have been made in conventional fuzzy systems, a few hybrid-fuzzy identification methods have been proposed. Palm and Driankov [37] present a hierarchical identification approach for fuzzy switched systems. The proposed method considers a black-box fuzzy identification approach by using fuzzy clustering and measurable discrete states in order to obtain the hybrid-fuzzy model. Although good performance is obtained, prior knowledge about the discrete modes is required. Next, Girimonte and Babuška [38] describe two structure-selecting methods for non-linear models with mixed discrete and continuous inputs. The first method, based on fuzzy clustering, uses fuzzy sets to obtain the relevant inputs. The second approach involves an induction algorithm included in a search method. The results show that fuzzy clustering is faster in terms of computation time. Zeng et al. [39] propose a new representation theorem for hierarchical systems when a discrete input space is considered. The theorem states that one-to-one mappings for low-level functions are required to obtain a flexible hierarchical representation. Moreover, they demonstrate that flexible hierarchical fuzzy systems satisfy the universal approximation property, which allows us to estimate any hierarchical function to any degree of accuracy. A new hierarchical structure of hybrid systems integrating modeling and control is presented by Cheng et al. [40], where the fuzzy controller is synthesized based on the identification of continuous and discrete components. The authors of [40] assume that measurements of the discrete components are available, which allows the use of fuzzy adaptive identification techniques or other ways to directly learn a TS model by clustering or by identifying a neuro-fuzzy model for each of the separate regions. In our paper, direct measurements of the discrete component are not available, and as a consequence it is not possible to do an experimental contrast within those other hybrid-fuzzy identification frameworks.

In this paper, a new identification method is proposed for nonlinear hybrid systems that identifies first the discrete transitions and then all other non-linearities through fuzzy models only using input–output data of the process, where the main difference with the literature is that prior knowledge of the discrete modes is not required. Next the hybrid-fuzzy models and the identification problem are presented.

2. Problem statement

For the modeling of hybrid systems two of the most popular model types used in the literature are piecewise affine (PWA) systems and mixed logical and dynamical (MLD) systems [11]. In this paper the use of another type of model called hybrid-fuzzy systems is proposed, which combine the characteristics of fuzzy models to represent nonlinearities, and of hybrid systems to include quantized variables.

A hybrid discrete-time nonlinear dynamic system is considered with input $\mathbf{u}(t) \in \mathbb{R}^m$, and to explain the identification method a single output $y(t) \in \mathbb{R}$ is assumed (the method is easily extendible for multiple outputs). Let $\mathbf{u}^{t-1} = [\mathbf{u}^T(t-1), \ldots, \mathbf{u}^T(t-n_b)]^T \in \mathbb{R}^{m \cdot n_b}$ be past inputs, and $\mathbf{y}^{t-1} = [y(t-1), \ldots, y(t-n_a)]^T \in \chi \subset \mathbb{R}^{n_a}$ be past outputs, up to time $t-1$, where n_a and n_b are the model orders (given a priori). The class of hybrid systems considered is described as:

$$\begin{aligned} y(t) &= \sum_{i=1}^{s} f_i(\mathbf{y}^{t-1}, \mathbf{u}^{t-1}) \varrho_i(\mathbf{y}^{t-1}), \\ \varrho_i(\mathbf{y}^{t-1}) &= \begin{cases} 1, & \text{if} \quad \mathbf{y}^{t-1} \in \chi_i \\ 0, & \text{otherwise} \end{cases}, \end{aligned} \tag{1}$$

where s is the number of discrete modes (submodels). The local behavior of the system is described by the functions $f_i(\cdot)$ and the discrete mode $\varrho_i(\mathbf{y}^{t-1})$ is a binary variable that equals 1 if $\mathbf{y}^{t-1}$ belongs to the region of $\chi_i \subset \mathbb{R}^{n_a}$, and 0 otherwise. The regions χ_i form a complete partition of the regressor set χ, i.e. $\bigcup_{i=1}^{s} \chi_i = \chi$ and $\chi_i \cap \chi_j = \emptyset$, $\forall i \neq j$. Note that discrete dynamics (transitions) of the system are assumed to occur when $\mathbf{y}^{t-1}$ satisfies some conditions, and they will not depend on the inputs. The aim in this work is to present a systematic method for determining the functions $f_i(\cdot)$ and the regions χ_i given only the input–output data of the process. The functions $f_i(\cdot)$ could be any non-linear function that will be identified by the TS models and the regions χ_i are assumed to be convex polyhedra, described by

$$\chi_i = \{\mathbf{y}^{t-1} \in R^{n_a} : H_i \mathbf{y}^{t-1} \preceq h_i\} \tag{2}$$