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E2GKpro: An evidential evolving multi-modeling approach for system behavior prediction with applications

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ABSTRACT

Nonlinear dynamical systems identification and behavior prediction are difficult problems encountered in many areas of industrial applications, such as fault diagnosis and prognosis. In practice, the analytical description of a nonlinear system directly from observed data is a very challenging task because of the too large number of the related parameters to be estimated. As a solution, multi-modeling approaches have lately been applied and consist in dividing the operating range of the system under study into different operating regions easier to describe by simpler functions to be combined. In order to take into consideration the uncertainty related to the available data as well as the uncertainty resulting from the nonlinearity of the system, evidence theory is of particular interest, because it permits the explicit modeling of doubt and ignorance. In the context of multi-modeling, information of doubt may be exploited to properly segment the data and take into account the uncertainty in the transitions between the operating regions. Recently, the Evidential Evolving Gustafson–Kessel algorithm (E2GK) has been proposed to ensure an online partitioning of the data into clusters that correspond to operating regions. Based on E2GK, a multi-modeling approach called E2GKpro is introduced in this paper, which dynamically performs the estimation of the local models by upgrading and modifying their parameters while data arrive. The proposed algorithm is tested on several datasets and compared to existing approaches. The results show that the use of virtual centroids in E2GKpro account for its robustness to noise and generating less operating regions while ensuring precise predictions.

1. Introduction

1.1. Nonlinear systems and multi-model approaches

Dealing with nonlinear systems behavior identification and prediction is a widely encountered problem in real world applications in engineering, industry, time series analysis, prediction and fault diagnosis [1]. Modeling their behavior from observed data is a difficult task to perform because the identification of nonlinear systems involves a large number of related parameters to be estimated. Usually, a model consists in a set of functional relationships between the elements of a set of variables. One way to overcome the complexity related to nonlinearity is to adopt multi-model approaches [2–5].

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Using multi-model approaches is motivated by the difficulty, and sometimes the inability to analytically describes the system's behavior in its entire operating range. This problem can be considerably reduced by considering that the system's behavior gradually evolves along the operating range. Thus, the system could locally be described by simple functions corresponding to some operating regions. Such an approach can be seen as a weighted contribution of a set of models approximating the whole system's behavior, each of which is valid in a well defined interval or covers a part of the whole feature space of the problem to be solved. The description of the global system's behavior is then made by the combination of the local models. The contribution of each local model to the assessment of the multi-model's output is quantified by an *activation degree*. So, the general goal is to determine the contribution rate of each local model in order to minimize the identification error.

The identification task involves two steps: a structural and a parametric identification. The structural identification consists in determining the number of models and the associated activation degrees. It is based on the partitioning of the whole system's feature space and permits the specification of the structure of the local models. The parametric identification is performed to evaluate the parameters of the local models. One can use either a static or a recursive methodology [6].

1.2. Uncertainty management in multi-model approaches

Complex system dynamics often generate significant uncertainty, since understanding the response of nonlinear systems is a very challenging task. In engineering applications, it is very common that the input information to perform the desired analysis is qualitatively and quantitatively limited. Uncertainty sources are numerous and may take the form of system variability, environmental and operational conditions, data acquisition errors, among other sources that vary depending on the application at hand.

This imperfection of the data must be taken into account in the modeling process. In cases where uncertainty cannot be fully attributed to intrinsic variability (aleatory uncertainty), the uncertainty is said to be epistemic and is due to the lack of knowledge. Aleatory uncertainty refers to the inherent variation associated with the physical system under question and its environment and cannot be reduced, whereas epistemic uncertainty refers to the lack of knowledge or incomplete information regarding quantities or processes of the system or the environment. In any case, uncertainty quantification is required in order to understand the capabilities and limitations of the modeling process. While probability theory is well suited to deal with aleatory uncertainties (intrinsic variability), other formalisms exist that are more appropriate to manage epistemic uncertainty [7], among which, fuzzy sets or possibility theory and evidence theory, also known as belief functions theory [8] which are the most prominent ones.

In the context of multi-modeling, fuzzy set theory has been used to deal with imprecision within data [9,10]. Recently, fuzzy rule-based models of Takagi–Sugeno (TSK) type [11] have been widely used in modeling applications of complex systems, due to their flexibility and computational efficiency. TSK models are multi-models with fuzzily defined regions of validity of the local models. The main advantage of the TSK models is that since the local regions are fuzzily defined, the resulting global model can be nonlinear (of high order) while the local models can be very simple. Usually linear (first order) sub-models are considered [11,12].

A first order Takagi–Sugeno model can be seen as a multi-model structure consisting of linear models. It is based on a fuzzy decomposition of the input space. For each part of the state space, a fuzzy rule can be constructed to make a linear approximation of the input, and the global output is a combination of all rules. Then, the parameters of the models (nonlinear parameters of membership degrees and linear parameters for the consequent of each rule) are tuned in an appropriate learning procedure. Usually, the identification of the linear parameters is addressed by some gradient descent variant whereas nonlinear parameters are determined by a clustering of the input space. This kind of approach has been applied to build a neuro-fuzzy predictor in the context of prognosis application in [13]. It was based on the evolving extended Takagi–Sugeno system (exTS) proposed by Angelov and Filev [14].

1.3. On belief functions and their application in TS models

Ramdani et al. [15] exploited the theoretical framework of belief functions to deal with uncertainties in multi-modeling. The authors developed a multi-modeling strategy founded on a TSK fuzzy model. The basic idea was to consider a fuzzy rule-based system with a belief structure as output. The focal elements of each rule were formed by a subset of a collection of functional models, each of which was constructed based on a fuzzy model of Takagi–Sugeno type. The main advantage of this approach remains in the use of belief functions theory to determine the activation degrees of the local models because these functions have the particularity to enable the explicit modeling of doubt and ignorance. Their proposed methodology is an *offline* approach and requires the entire dataset to be available in advance for the modeling process.

In this paper, we propose to adapt the offline approach developed in [15] to make it online, in order to deal with sequential data, meaning that the data arrive gradually. In the sequel, we will use the word "evolving" to qualify an algorithm which is able to adapt its parameters online.

The proposed algorithm is called E2GKpro and relies on the Evidential Evolving Gustafson–Kessel algorithm (E2GK) initially developed in [16] to sequentially perform the clustering phase using the formalism of belief functions.