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Recursive fuzzy instrumental variable based evolving neuro-fuzzy identification for non-stationary dynamic system in a noisy environment

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Abstract

In this paper an online identification algorithm for instrumental variable based evolving neuro fuzzy modeling applied to dynamic systems in noisy environment, is proposed. The adopted methodology is based an online neuro-fuzzy inference system with Takagi–Sugeno evolving structure, which employs an adaptive distance norm based on the maximum likelihood criterion with instrumental variable recursive parameter estimation. The application and performance analysis of the proposed algorithm is based on black box modeling of a 2DOF Helicopter with errors in the variables.

Keywords: Evolving neuro-fuzzy; Takagi–Sugeno; Black box modeling

1. Introduction

Batch fuzzy clustering algorithms play an important role in modeling from experimental data. However, these algorithms require an initial condition from expert, that is, the number of initial fuzzy clusters so that the algorithm can be performed [1–3]. Furthermore, data clustering is the aim at major engineering problems in different areas such as manufacturing, control and signal processing, motivating the development of modeling methodologies [4,5].

An important problem in data clustering is the estimation of the number of clusters from a nonstationary data set, which is not a new issue, so there are several comprehensive works dealing with adaptive, incremental, evolving clustering [6–8] and the detecting of clusters with varying volume, uncertain shapes, unequal sizes and variable densities [3,4,9,10].

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In many case studies cited in the literature, it appears that the clustering task is not restricted to data sets in batch (*offline*), but it can be applied to nonstationary stream data set (*online*). Therefore, once these data structures are dynamic, the clustering algorithm should be able to evolve as data are read [11–14].

According to [15–18], the evolving models are data-driven models, which adapt automatically, dynamically extend and evolve the structure when a new sample data is read from dynamic system. So, evolving models are able of supporting time varying flow data and changing your nature over time and space [13,15,17]. Within the concept of evolving systems (models), there is the evolving fuzzy systems that combine the best features of fuzzy systems (universal approximation capabilities in connection with comprehensibility and understandability aspects) with concept of evolving systems [8,12,13,15,17,19].

In the XXI century, the first research in evolving fuzzy clusterings were based on Euclidean distance norm, and these algorithms employed norms of non-adaptive distances and consequently had its clustering compromised. After that, there were research in evolving fuzzy clustering which were based on norms of adaptive distances, such as Mahalonobis distance norm. Currently, the research on intelligent evolving systems, especially on evolving fuzzy inference systems, has been developed to enhance the ability to change the structure and parameters of fuzzy models. Recent developments in data stream clustering integrate dynamic split and merge concepts in order to overcome different structures of clusters [2,9,8,12,13,15,17,20–24] and arbitrary shaped rules (termed clouds), which is established in [12].

This paper proposes an evolving clustering algorithm based on maximum likelihood criterion with participatory learning and recursive parameter estimation with Fuzzy Instrumental variable which embeds auxiliar instrumental variables in the Recursive Least Squares (RLS) design, based on pre-filtered target (outputs) measurements and that is capable of adopting an adaptive search strategy to the experiment in order to avoid the problem of curse of dimensionality related to the number of rules created.

The originality of the proposed methodology can be considered as follows:

1) A strategy based on measures distance between the clusters centers that use maximum likelihood criterion to identify the similarity of two or more fuzzy rules and the merging of these rules into a single fuzzy rule in order guarantee the interpretability and transparence of the neuro-fuzzy model, different the merging concepts in the papers [25–27];
2) The use of fuzzy instrumental variable, in the evolving context, for robust estimation of consequent parameters in spite of correlated noise in the experimental data, especially in cases of low signal to noise ratios (due to high noise levels), which means that it is not necessary detailed information on the noise statistics and, consequently, it does not require noise model [28–30];
3) Evolving participatory learning based on adaptive norm, different to the well-known evolving participatory learning approach (ePL) for training fuzzy systems, as proposed in [18,31].

The main contributions of the proposed methodology can be considered as follows:

1) An initial neuro-fuzzy model based on batch estimation from an *off-line* data set, which significantly improves robustness and quality of predictions, especially during the first couples/dozens of *online* stream samples and furthermore assure some more trustfulness of experts in applications, when they want to see a reliable model first with some understandable knowledge behind;
2) Evolving identification Neuro-Fuzzy models based on maximum likelihood adaptive norm;
3) A new approach for recursive consequent learning which embeds auxiliar instrumental variables in the recursive least squares (RLS) design, based on pre-filtered target (outputs) measurements, leading to higher stability of the solutions than when using standard RLS, especially in cases of low signal to noise ratios (due to high noise levels).

The outline of the paper is as follows. Section 2 provides the general problem formulation of the evolving neuro-fuzzy proposed. The convergence proof of the fuzzy instrumental variable which embeds auxiliar instrumental variables in the Recursive Least Squares (RLS) design, based on pre-filtered target (outputs) measurements is described in Section 3. In the Section 4, the proposed methodology was applied to nonlinear system identification and compared with evolving fuzzy modeling approaches widely cited in the literature. In Section 5, a black box modeling