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On-line Evolving Cloud-based Model Identification for Production Control

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Abstract:
In this paper we present an on-line evolving fuzzy cloud-based identification method. The evolving part of the algorithm is improved with new mechanisms. In the part of adding clouds (fuzzy rules) a new condition is implemented in addition to existing ones. Moreover, completely new mechanism for removing the "less active" and "less informative" clouds is introduced. All these mechanisms prevent adding new clouds based on outliers or at least help deleting existing ones with little information. The cloud-based method uses vectorized non-parametric antecedent (**IF**) part which relies on the local density of the current data with the existing clouds. The parameters of the consequent (**THEN**) part (functional in this case) were identified using recursive Weight Least Square method.
The comparison between the original and the improved algorithm was provided on simulated data input/output signals acquired from Tennessee Eastman (TE) benchmark process. Firstly, most representative production Performance Indicators (pPIs) were chosen, then for each pPI a model was identified. The provided results (quality measures) of the proposed method were evaluated using on-line and off-line 4-step prediction. These were further compared with the results obtained using eFuMo identification tool.

Keywords: Cloud-based identification, evolving system, production control, Tennessee Eastman process

1. INTRODUCTION

Controlling a modern production systems requires not only the basic technological functions but also model based (data-driven) control of influential performance indicators of interest. The new developments of predictive manufacturing (Lee et al., 2013) tend to improve the functionality and effectiveness by exploiting knowledge contained in the collected data. Other analysis methods are applied to fault detection and diagnosis for industrial process operation (Qin, 2012; Zhang et al., 2015). The applicability of the data-based methods could be improved by considering the system dynamics. Model based fault detection combines the data-driven methods with model-based approaches (Precup et al., 2015). As dynamic models are required, the system identification methods play a crucial role.

Fuzzy modeling is well established technique for approximating and describing complex and non-linear system behavior. One of the most popular tool is Takagi-Sugeno (TS) fuzzy model (Takagi and Sugeno, 1985). Constructing the TS model requires identifying of the membership functions of the antecedent part and the local model's parameters of the consequent part. The identification of such models can be done in an on-line or an off-line manner. In the past few decades a significant number of on-line identification techniques were proposed relying on fuzzy logic (eTS by Angelov and Filev (2004), exTS by Memon et al. (2006), FLEXFIS by Lughofer and Klement (2005), switching eTS by Kalhor et al. (2013), etc.).

Simplest form for the antecedent part was proposed by Angelov and Yager (2011). This new fuzzy rule based (FRB) system, named ANYA, uses non-parametric vectorized antecedent part. It is based on data clouds (sets of previous data samples close to each other) while the membership functions are calculated using relative data density of the current data with the existing clouds. Moreover, the method is able to evolve the structure (adding new fuzzy rules). Originally the evolving mechanism relies on global data density, while in this paper just local density threshold is used. In the recent years ANYA FRB system was used for solving control problems (Angelov et al., 2013; Škrjanc et al., 2014; Costa et al., 2013; Andonovski et al., 2015b) and as a tool for model identification (Rosa et al., 2014; Ali et al., 2012; Blažič et al., 2014, 2015).

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In this paper we propose an improved evolving mechanisms for protecting of adding new clouds (rules) based on outliers. Moreover, a new mechanism for removing "less active" and "less informative" clouds is introduced. The *activity* is a property of the cloud and it is defined as relative number of the data samples associated with particular cloud from its creation. While the other mechanism delete the clouds which obtained less information in comparison with the other clouds.

The proposed cloud-based identification method was tested on input/output data acquired from Tennessee Eastman (TE) (Downs and Vogel, 1993) process model. The TE system is a complex nonlinear, open-loop unstable process and it consists of 41 measured and 12 manipulative variables. Please refer to (Downs and Vogel, 1993) for detail description of the TE process. The production objectives of the systems are usually defined through the production performance indicators (pPIs). For the TE process as the first pPI, an estimation of the production *Cost* was defined by Downs and Vogel (1993). In the (Glavan et al., 2013a,b) the other two pPIs were defined as *Production* and *Quality*. Furthermore, the authors selected the most relevant manipulative input variables (see Table 1).

Table 1. Process manipulative variables selected by Glavan et al. (2013b).

Notation	Controlled variable setpoints
F_p	Production rate index
R_2	Striper level
R_3	Separator level
R_4	Reactor level
R_5	Reactor pressure
R_7	$\%C$ in purge
R_8	Recycle rate
R_9	Reactor temperature
r_2	D/E feed rates

This paper is organized as follows. In Section 2 the cloud-based identification method is presented, while in Section 3 an improved evolving mechanism for adding and removing clouds is presented. Section 4 introduces the experimental results and at the end, in Section 5 the main ideas and results are concluded.

2. CLOUD-BASED IDENTIFICATION OF A DYNAMIC SYSTEM

2.1 Fuzzy rule-based model

Fuzzy systems are sufficient approximation tools for modeling non-linear dynamic processes. In this paper we use the fuzzy rule-based system with non-parametric antecedent part presented by Angelov and Yager (2011). The main difference is the simplified antecedent part which relies on the data relative density. The rule-based form of the i^{th} rule is defined as:

$$\mathcal{R}^i : \text{IF} \quad (\boldsymbol{x}_f \sim X^i) \quad \text{THEN} \quad y_i(k) = f_i(\boldsymbol{x}_f) \tag{1}$$

where the data sample (regression vector) is $\boldsymbol{x}_f(k) = [y(k-1), \ldots, y(k-n_a), u(k-1), \ldots, u(k-n_b)]$ for partitioning of the problem space and the variables y and u denote system input and output, respectively. The operator $\sim$ is linguistically expressed as '*is associated with*', which means that the current data $\boldsymbol{x}_f$ is related with one of the existing clouds X^i according to the membership degree (normalized relative density of the data). The input and the output order are denoted with n_a and n_b, respectively. Note that the input $u(k)$ does not have immediate influence to the output $y(k)$. The partial NARX model of the i^{th} rule is defined as:

$$f_i(k) = \boldsymbol{\theta}_i^T \boldsymbol{\psi}_k \tag{2}$$

where the vector $\boldsymbol{\psi}_k = [\boldsymbol{x}_f,\, 1]^T$ consists of the regression vector $\boldsymbol{x}_f$ (used for partitioning the data space) to which we usually add a regressor 1. The vector of parameters of the i^{th} cloud (rule) is denoted as $\boldsymbol{\theta}_i^T = \left[a_1^i, \ldots, a_{n_a}^i,\, b_1^i, \ldots, b_{n_b}^i,\, r^i\right]$. Once we have declared all the parameter vectors $\boldsymbol{\theta}_i^T$ for each cloud $(i = 1, \ldots c)$ we could define the output of the system in a compact matrix form:

$$y(k) = \sum_{j=1}^{c} \beta^j(\boldsymbol{x}_f)\boldsymbol{\theta}_j^T \boldsymbol{\psi}_k = \boldsymbol{\beta}^T(\boldsymbol{x}_f)\boldsymbol{\Theta}^T \boldsymbol{\Psi}(k) \tag{3}$$

where c is the number of clouds (fuzzy rules), $\boldsymbol{\beta}^T(\boldsymbol{x}_f) = \left[\beta^1,\, \beta^2, \ldots, \beta^c\right]$ is the vector of normalized relative densities determined between the current data $\boldsymbol{x}_f$ and all existing clouds, and $\boldsymbol{\beta}^T$ will be discussed in next subsection. The matrix $\boldsymbol{\Theta} = [\boldsymbol{\theta}_1,\, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_c] \in \mathbb{R}^{(1+n_a+n_b)\times c}$ contains the vectors of parameters for all the existing clouds [1].

2.2 Identification of the antecedent part

In this subsection we will describe identification method of the non-parametric antecedent part of the fuzzy rule-based system ANYA (Angelov and Yager (2011)). The method starts with zero fuzzy rules (clouds) and the first cloud is initialized with the first data $\boldsymbol{x}_f$ received. For each of the following data the normalized relative densities β^i are calculated and then the current data is associated with one of the existing clouds (according to the maximal density β^i, where $i = 1, \ldots c$) or a new cloud is added (evolving mechanism).

Before calculating the vector $\boldsymbol{\beta}$ we need to calculate the local relative density which is defined by a suitable kernel over the distances between the current data $\boldsymbol{x}_f(k)$ and all the data previously associated with the cloud. The Euclidean distance ($d_{kj}^i = \|\boldsymbol{x}_f(k) - \boldsymbol{x}_f^i(j)\|$) was chosen in this case (also used by Angelov and Yager (2011), Angelov et al. (2013), Škrjanc et al. (2014)), but any other distance could be also used, e.g. Mahalanobis distance was used by Blažič et al. (2014) and Blažič et al. (2015).

The local density γ_k^i of the current data $\boldsymbol{x}_f(k)$ with the i^{th} cloud is defined by Cauchy kernel as follows:

$$\gamma_k^i = \frac{1}{1 + \frac{\sum_{j=1}^{M^i} (d_{kj}^i)^2}{M^i}} \tag{4}$$

where M^i is the number of the data points that belong to the i^{th} cloud. Equation (4) should be rewritten in recursive form for easier implementation as follows:

$$\gamma_k^i = \frac{1}{1 + \|\boldsymbol{x}_f(k) - \boldsymbol{\mu}_k^i\|^2 + \sigma_k^i - \|\boldsymbol{\mu}_k^i\|^2} \quad i = 1, \ldots, c \tag{5}$$

[1] We use the therm of 'existing clouds' because this method evolves and number of clouds changes when some requirements are fulfilled.