Comparison of Two On-line Hybrid System Identification Methods

T. Alizadeh, A. Alizadeh, S. Sepasi, S. Barzegary

***Abstract*— In this paper we compare two recently proposed algorithms for online identification of hybrid systems. We consider the adaptive growing and pruning Radial Basis Function (RBF) neural network based and the potential fuzzy clustering based procedures. Specific behaviors of the procedures are pointed out, using a well known two dimensional example.**

***Index Terms*— Hybrid systems – identification – GAPRBF neural network – potential Fuzzy Clustering.**

I. Introduction

In recent years, the interest in the area of hybrid systems has grown widely. Hybrid systems arise when the continuous dynamics, driven by physical laws, and discrete dynamics, driven by logical rules, coexist and interact with each other. Thus, hybrid models describe processes that evolve according to dynamic equations and logic rules. Most of the literature on hybrid systems has dealt with control, stability analysis, verification and fault detection based on the availability of a model for the hybrid system. Getting such a model from a given input-output data is an identification problem.

The existing identification approaches for the hybrid systems can generally be classified into the variants of the Mixed-Integer Programming (MIP) approach [1], clustering-based approaches [2], the bounded-error approach [3], the Bayesian approach [4], the algebraic approach [5] and neural network based approaches [6]. The comparison between three [7] and four [8] identification methods have been done previously. Most of the mentioned methods are offline, however in this paper, two recently proposed online identification algorithms are compared, adaptive growing and pruning RBF neural network based [9] and potential fuzzy clustering based procedures [10]. In order to compare the methods, the procedures are applied to identify a well known hybrid system. The rest of the paper is organized as follows. A brief summary of the identification methods are given in section 2. In section 3, a benchmark system is identified using both algorithms and the identification results are compared. Finally the conclusions are given in section 4.

Manuscript received December 26, 2009.

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II. The Compared Procedures

Finding an appropriate model for given input-output data is an identification problem. Most of the proposed identification algorithms assume a model and try to obtain the models parameters in order to have a suitable model, however, the methods considered in this paper, are both black box models. The structure of the model is not fixed and it could be changed during identification. In this section we briefly discuss the adaptive growing and pruning RBF neural network based and potential fuzzy clustering based procedures.

A. Adaptive growing and pruning RBF neural network based method

To the best of our knowledge, the ability of neural networks to identify a global parametric model for a class of hybrid systems has been demonstrated in [6] for the first time. In this contributed paper, feed-forward neural networks were used for offline identification of a benchmark hybrid system. Due to their ability to approximate complex nonlinear mappings directly from the input output data with a simple topological dynamic structure, Radial Basis Function (RBF) neural networks have been popularly used in many identification applications in recent years. Huang et al. [11] have recently proposed a simple sequential learning algorithm with network growing and pruning (GAP) capabilities. The complete description of the adaptive GAPRBF neural network based hybrid system identification method can be summarized as follows:

The learning algorithm begins with no initial hidden neurons. As each new observation data (x_n, y_n), where $x_n \in R^l$, are received the following steps are performed:

1. **Compute** the overall network output:

$$f(x_n) = \sum_{k=1}^{K} \alpha_k \phi_k(x_n) \qquad (1)$$

where K is the number of hidden neurons , α_k is the connecting weight of the *k*th hidden neuron to the output neuron. $\phi_k(x_n)$ denotes response of the *k*th hidden unit to the input vector x_n, defined by the following Gaussian function:

$$\phi_k(x_n) = \exp\left(-\frac{\|x_n - \mu_n\|^2}{\sigma_k^2}\right) \qquad (2)$$

ISBN: 978-988-18210-4-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

where μ_k and σ_k refer to the center and width of the *k*th hidden neuron respectively and $\|\cdot\|$ indicates the Euclidean distance.

2. **Calculate** the parameters required in the modified growth criterion:

$$\varepsilon_n = \varepsilon_{\min} + (\varepsilon_{\max} - \varepsilon_{\min})(1 - e^{-n/\tau}) \quad (3)$$

where τ is the time constant parameter that can be used to control the time rate evolution of ε_n . $\varepsilon_{\min}$ and $\varepsilon_{\max}$ are minimum and maximum distance thresholds, respectively.

$$e_n = y_n - f(x_n) \quad (4)$$

1. **Apply** the growth criterion for adding neurons:

$$\text{If } |e_n| > e_{\min} \text{ and } \|x_n - \mu_{nr}\| > \varepsilon_n \text{ and } \left(1.8\kappa \|x_n - \mu_{nr}\|^l\right)|e_n| / S(X) > e_{\min} \quad (5)$$

(where $e_{\min}$ is the expected desired accuracy and μ_{nr} is the center of the nearest neuron to x_n and $S(X)$ is the estimated size of range (X) where the training samples are drawn from)

Allocate a new hidden K+1 with:

$$\alpha_{K+1} = e_{\min}$$
$$\mu_{K+1} = x_n \quad (6)$$
$$\sigma_{K+1} = \kappa \|x_n - \mu_{nr}\|.$$

Else

Adjust the network parameters $\alpha_{nr}, \mu_{nr}, \sigma_{nr}$ for the nearest (nrth) neuron only, using the UKF algorithm.

Check the modified pruning criterion for the nearest (nrth) hidden neuron:

If $\left|(1.8\sigma_{nr})^l \alpha_{nr} / S(X)\right| < \beta\, e_{\min}$, (in which a new pruning factor $0 < \beta \le 1$ has been added), remove the nearest (nrth) hidden neuron and do the necessary changes in the UKF algorithm.

Endif

Endif

For network parameter estimation, modified UKF learning algorithm has been used which is not investigated here.

B. Potential fuzzy clustering based procedure

Like neural networks, Takagi-Sugeno (TS) fuzzy models, have been popularly used in many applications in recent years. TS fuzzy models can be described by:

r_i : if (x_1 is M_{i1}) and . . . and (x_n is M_{in}) then (

$$y_i = a_{i0} + a_{i1}x_1 + \ldots + a_{in}x_n); \ \text{i}=\{1,\ldots, \text{R}\} \quad (7)$$

where r_i denotes the ith fuzzy rule, R is the number of fuzzy rules, $x = [x_1, x_2, ..., x_n]^T$ is the input vector, M_{ij} indicates the antecedent fuzzy sets, j = {1,…, n}, yi is the output of the ith linear subsystem, and ail ; l={0,…, n}, are its parameters.

Model structure identification includes estimation of the focal points of the rules by fuzzy clustering [8]. In aTS, the rule-base is assumed to be gradually changing. Therefore, the number of rules as well as the parameters of the antecedent part will vary.

The on-line potential clustering procedure starts with the first data point established as a focal point of the first cluster. Its coordinates are used for the antecedent part of the fuzzy rule, using the following Gaussian membership functions:

$$\mu_{ij} = e^{-\alpha\left\|x_j - x_{ij}^*\right\|^2}; \ \text{i} = \{1,\ldots, \text{R}\}, \text{j} = \{1,\ldots, \text{n}\} \quad (8)$$

where $\alpha = 4/r^2$ is a positive constant, defining the spread of the antecedent and the zone of influence of the model and x_{ij}^* is the focal point of the ith rule antecedent. As a result, the potential of the first data point will be equal to 1.

Following the procedure from the next data point onwards, the potential of the new data points (z_k) is calculated recursively as follows [8]:

$$P_k(z_k) = \frac{k-1}{(k-1)(\vartheta_k + 1) + \sigma_k - 2\upsilon_k} \quad (9)$$

where $\vartheta_k = \sum_{j=1}^{n+1}(z_k^j)^2$; $\sigma_k = \sum_{l=1}^{k-1}\sum_{j=1}^{n+1}(z_l^j)^2$; $\upsilon_k = \sum_{j=1}^{n+1} z_k^j \beta_k^j$; $\beta_k^j = \sum_{l=1}^{k-1} z_l^j$, and z_ℓ^j denotes the data point on the axis z^j (x^j for j =1, 2, . . . , n and on the axis y for j = n+1). Parameters ϑ_k and υ_k in (9) are calculated from the current data point z_k , while β_k^j and σ_k are recursively updated as $\sigma_k = \sigma_{k-1} + \sum_{j=1}^{n+1}(z_{k-1}^j)^2$; $\beta_k^j = \beta_{k-1}^j + z_{k-1}^j$.

The recursive formula for updating the potentials of the focal points of the existing clusters can easily be derived from (9):

$$P_k(z_l^*) = \frac{(k-1)P_{k-1}(z_l^*)}{k - 2 + P_{k-1}(z_l^*) + P_{k-1}(z_l^*)\sum_{j=1}^{j}(d_{k(k-1)}^j)^2} \quad (10)$$

where $P_k(z_l^*)$ is the potential at time k of the cluster center, which is a prototype of the lth rule and $d_{lk}^j = z_l^j - z_k^j$ denotes projection of the distance between two data points (z_l^j and z_k^j) on the axis z^j . Potentials of the new data points are compared to the updated potential of the centers of the existing clusters. If the potential of the new data point is higher than the potential of the existing centers, then the new data point is accepted as a new center and a new rule is formed with a focal point based on the projection of this center on the axis x (R:=R+1; $x_R^* = x_k$). If in addition to the previous condition, the new data point is close to an old center, based on the following measure satisfaction:

$$\frac{P_k(z_k)}{\max_{l=1}^{R} P_k(z_i^*)} - \frac{\delta_{\min}}{r} \ge 1 \quad (11)$$

ISBN: 978-988-18210-4-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Then the new data point (z_k) replaces this center ($z_j^* := z_k$). This mechanism for rule-base adaptation, called as modification, ensures a replacement of a rule with another one built around the projection of the new data point on the axis x. For consequence parameter identification, a RLS based approach has been used. There was also a new rule reduction algorithm to control the number of the generated rules.

III. Experimental Examples

In this section, the mentioned methods have been used to identify a PWARX benchmark model. The following PWARX model is considered [10]:

$$y_k = \begin{cases} -0.4y_{k-1} + u_{k-1} + 1.5 + e_k, \\ \quad if\ 4y_{k-1} + u_{k-1} + 10 \prec 0 \\ 0.5y_{k-1} - u_{k-1} - 0.5 + e_k, \\ \quad if\ 4y_{k-1} + u_{k-1} + 10 \geq 0 \\ \quad \text{and}\ 5y_{k-1} + u_{k-1} - 6 \leq 0 \\ -0.3y_{k-1} + 0.5u_{k-1} - 1.7 + e_k, \\ \quad if\ 5y_{k-1} + u_{k-1} - 6 \geq 0 \end{cases} \quad (12)$$

The input u_k and the noise e_k are white noises generated from uniform distributions over the intervals [−5, 5] and [−0.1, 0.1], respectively. 200 data points are available as depicted in figure 1 [10].

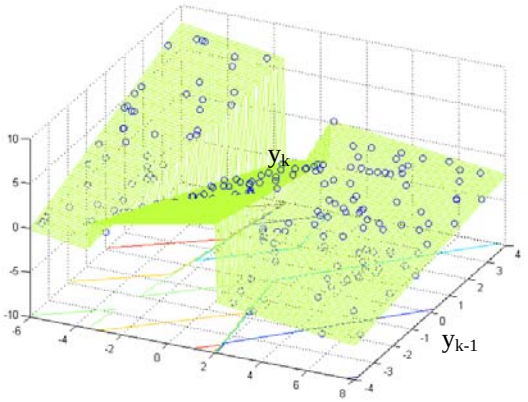

Figure 1. Data points used for identification

u_{k-1} and y_{k-1} are used as inputs of the MGAP-RBF neural network. Identification is performed using just one hidden neuron and the identification error is very small compared to previous results (neglecting a few points, identification error is between -0.007 and 0.007), as shown in figures 2a-2d.

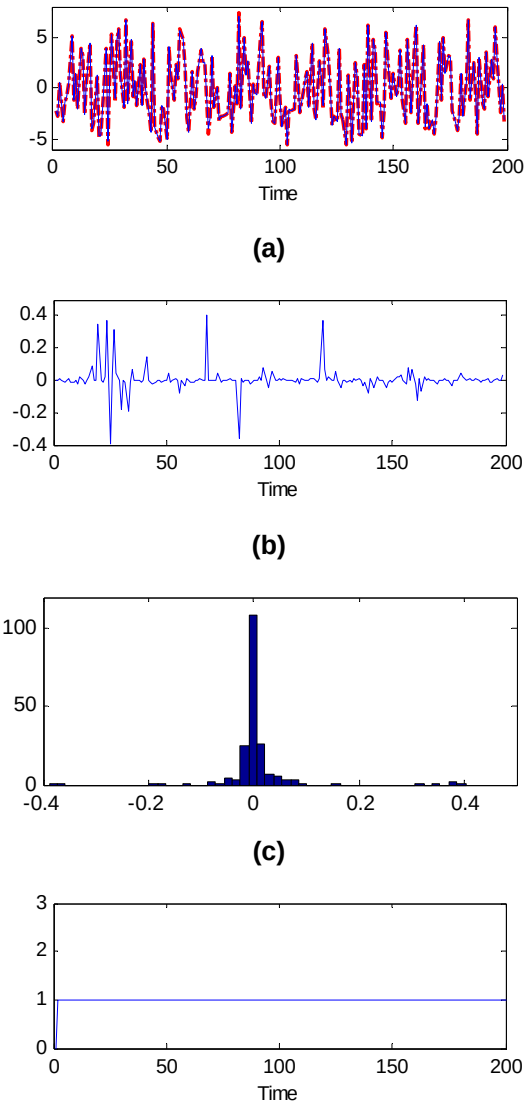

Figure 2. Predicted and measured outputs (a), identification residuals (b), distribution of the error residuals (c) and hidden neuron evolution (d).

The real identification data together with the estimated output and identification residual using the online potential fuzzy clustering approach have been shown in Figs. 3(a) and 3(b) respectively. The distribution of the identification error is shown in Fig. 3(c). As shown, the resulting residual is small enough and acceptable. The time changing of the generated fuzzy rules is presented in Fig. 3(d).

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ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

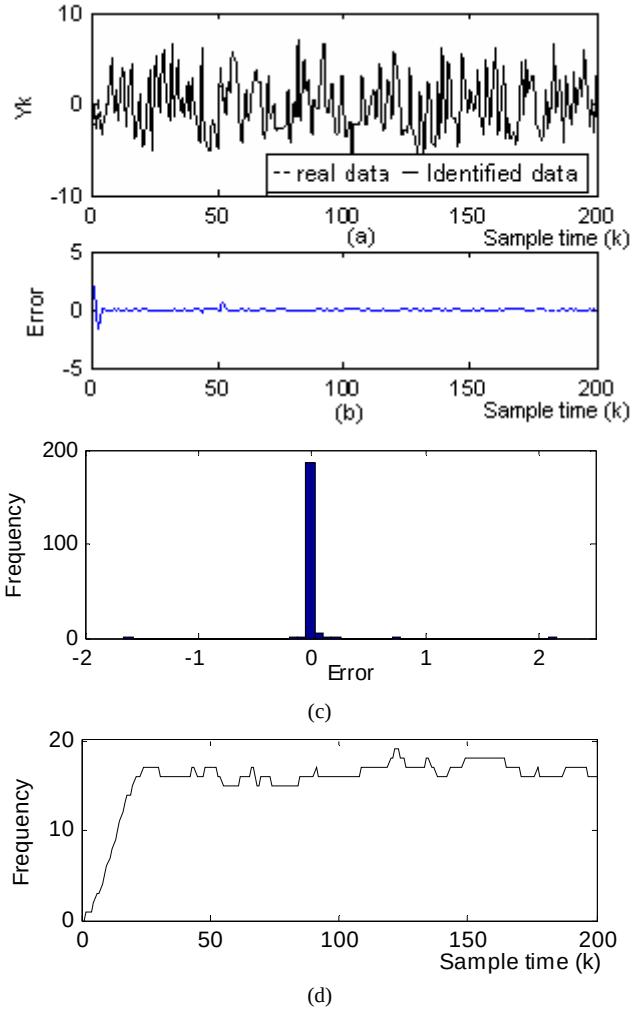

Fig. 3. Identification results for PWARX model

By investigating the identification results of the two approaches, it seems that the accuracy of the potential fuzzy clustering based approach is more than the GAPRBF neural network based one. Of course, on the other hand, it seems that the structure of the neural network is simpler than the achieved fuzzy system.

IV. Conclusions and Recommendations

In this paper, we discussed two approaches for the online identification of hybrid systems. Both approaches consider the identification data as a black box system without any apriori knowledge. Applying the identification methods on a benchmark PWARX model, it is shown that the identification error is smaller for the potential fuzzy clustering approach than the GAPRBF based neural network method. Although, it seems that the structure of the obtained neural network is simpler that the achieved fuzzy system. In this paper, the identification error just has been considered for comparison between the procedures; however, there should be better and reliable criteria for this purpose. Finding and applying such a criterion could be the subject of the future works.

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ISBN: 978-988-18210-4-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)