IDENTIFICATION IN ADAPTIVE CONTROL, NEURAL NETWORK FOR LINEAR MODEL PARAMETER ESTIMATION

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ABSTRACT

This paper deals with problems connected with identification in adaptive control. Firstly, it examines the relation between the classical recursive identification algorithms and the new approach based on neural networks. Furthermore, it illustrates these identification algorithms and compares it with the practical example. And finally it mentioned the neural network usable for parameter estimation of the linear model.

1 INTRODUCTION

Identification is the most problematic part in adaptive control. The major condition for success in adaptive control is the correct use of the identification. The fundamental issue is a appropriate choice of the sampling time. Additionally there are other aspects which have significant influence on control system, such as quantization effect in real process, disturbances, noise and other. However, the classical recursive identification algorithms cannot deal with them, therefore this paper investigates the identification based on neural networks.

2 PROCESS IDENTIFICATION

Adaptive controllers use the process model, which is estimated of actual inputs and outputs of the process and its parameters are further utilized to update the controller parameters and the controller action. The parameters of the model and the controller are updated in every sample time T_s.

The process model is mainly described as the linear time-invariant model:

$$\hat{y}_k = \varphi_k^T \boldsymbol{\theta}_k \tag{1}$$

where φ_k is a vector of measured inputs and outputs (regression vector) and $\boldsymbol{\theta}_k$ is a vector of the model parameters. In case of ARX model

$$\hat{y}_k = \sum_{i=1}^{m} b_i u_{k-i} - \sum_{j=1}^{n} a_j y_{k-j} \tag{2}$$

where b_i, a_j are model parameters, u_k process input and y_k process output, the vector of measured inputs and outputs is in form

$$\varphi_k = \begin{bmatrix} u_{k-1} & \ldots & u_{k-1-m} & -y_{k-1} & \ldots & -y_{k-1-n} \end{bmatrix}^T \tag{3}$$

and vector of model parameters

$$\boldsymbol{\theta}_k = \begin{bmatrix} b_{1_k} & \ldots & b_{m_k} & a_{1_k} & \ldots & a_{n_k} \end{bmatrix} \tag{4}$$

2.1 CLASSICAL IDENTIFICATION ALGORITHMS

The classical identification methods based on the Recursive Least-Mean-Square (RLS) algorithm are extended in adaptive control. The parameters of the process model are online updated via actual inputs and outputs of the real process in every sampling time k. The RLS identification with exponential forgetting is used in this paper:

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \mathbf{K}_{k+1}(y_k - \varphi_k^T \boldsymbol{\theta}_k) \tag{5}$$

where $\mathbf{K}_k$ is vector of correction

$$\mathbf{K}_{k+1} = \mathbf{P}_k \varphi_{k+1} \left[\lambda + \varphi_{k+1}^T \mathbf{P}_k \varphi_{k+1} \right]^{-1} \tag{6}$$

and $\mathbf{P}_k$ covariance matrix, $0 < \lambda \le 1$ is forgetting factor

$$\mathbf{P}_{k+1} = \mathbf{P}_k - \mathbf{K}_{k+1} \varphi_{k+1}^T \mathbf{P}_k \tag{7}$$

Advantage of these methods is fast convergence of the model parameters. Conversely, the significant defect is a long sample time necessary for the suitable identification which can result in improper behaviour of the whole control system. The long sampling period also results in a problem with an aliasing and it introduces unintentional additional dynamics in control system. Hence, it is suggested to investigate into identification of new methods.

2.2 IDENTIFICATION BASED ON NEURAL NETWORKS

One of the possibilities in process identification is to use the neural networks approach to the process identification. However, their generalization property can be employed for more stable identification solution.

The disadvantage when using neural networks in identification of adaptive controller is that the neural network is generally nonlinear system although it shall be used to estimate linear model parameters.

This problem can be resolved by several means. Firstly by using a single neuron, whose weights are directly parameters of the linear process model [1], [2] or secondly by using of a neural network with one hidden layer whose input is the regression vector (3) and output is the estimated vector of the model parameters (4) (fig. 1).

Using the most extended on-line training algorithm backpropagation the neural network weights $\mathbf{w}_k$ are updated in every sample time k as

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta_k \cdot \frac{\partial E_k}{\partial \mathbf{w}_k} + \alpha(\mathbf{w}_k - \mathbf{w}_{k-1}) \tag{8}$$

where η_k is the learning-rate parameter vector, α is momentum constant. These parameters have an influence on the rate of convergence. The parameters should be limited to interval (0, 1).

The lost function of the neural network is given according to (1):

$$E_k = \frac{1}{2}\sum_{i=1}^{m+n}(\hat{y}_k - y_k)^2 = \frac{1}{2}\sum_{i=1}^{m+n}\left(\varphi_k^T \boldsymbol{\theta}_k - y_k\right)^2 \tag{9}$$

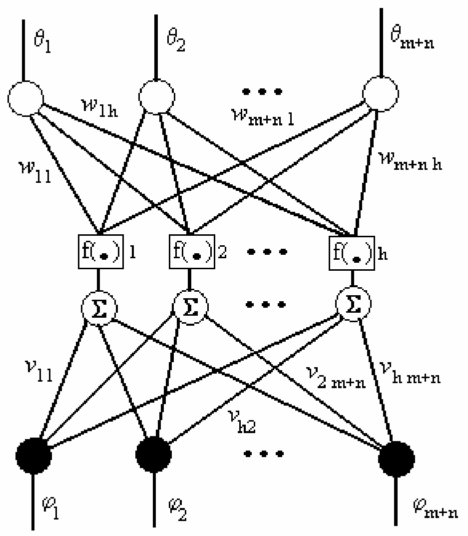

Fig. 1: *Neural network usable for parameter estimation of the linear model*

3 PRACTICAL RESULTS

The neural network usable for parameter estimation of the linear model was tested for process with transfer function

$$F_p(s) = \frac{1}{(s+1)(s+1)(10s+1)} \tag{10}$$

and using Takahashi controller

$$\begin{gathered} u_k = K_p(y_{k-1} - y_k) + K_I(d_k - y_k) + K_D(2y_{k-1} - y_{k-2} - y_k) + u_{k-1} \\ K_P = 0{,}6K_U,\ K_I = \frac{1.2K_U T_s}{T_U},\ K_D = \frac{3K_U T_U}{40T_s} \end{gathered} \tag{11}$$

where u_k is the control action, d_k desired value, y_k the process output, K_U ultimate gain and T_U ultimate period (Z-N method), T_s sample time.

In the real process it is necessary to take into account not only disturbances, noise and other nonlinearities influencing the process but also a quantization effect. The quantization effect affects quality of control system because the process input and output values are reduced to imprecise values according to the type of A/D and D/A converters.

In Fig. 2, Fig. 3 there are compared the both identification approaches by attendance of the quantization effect and the disturbance affecting the control system. The influence of the choice of the sample period is shown in Fig. 3.

The advantage of using neural network for process identification or model parameter estimation is shown until it is controlled the real process when the classical identification fails.

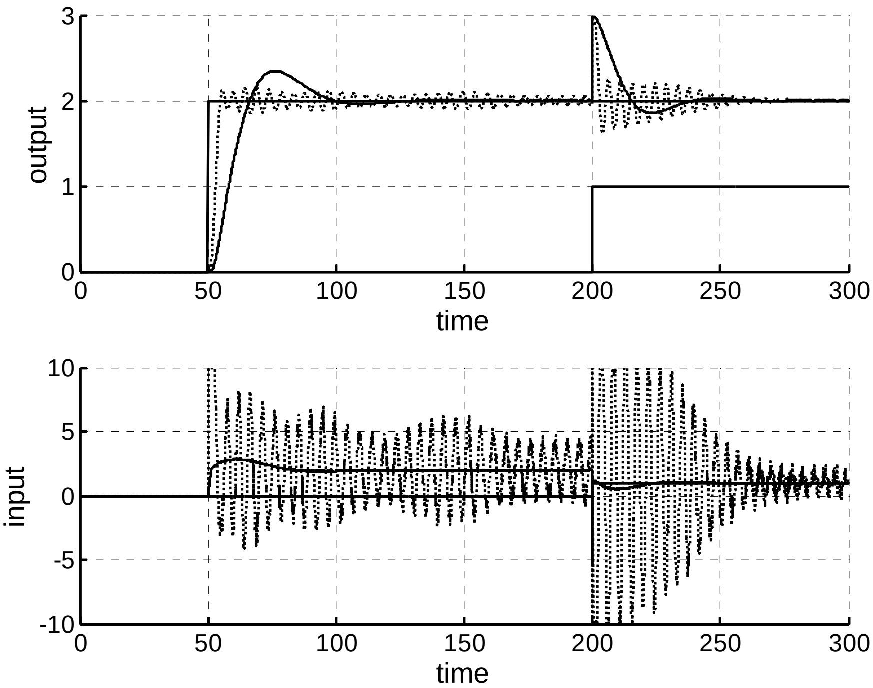

Fig. 2: *Takahashi controller with RLS identification (dotted lines) and with neural network based identification -* $T_s = 0.1$, $h = 6$, $\eta = 0.002$, $\alpha = 0.1$ *(solid lines) using 12 bits A/D and D/A converters. Desired value is set to +2 at time 50 s, at time 200 s disturbance +1 influences*

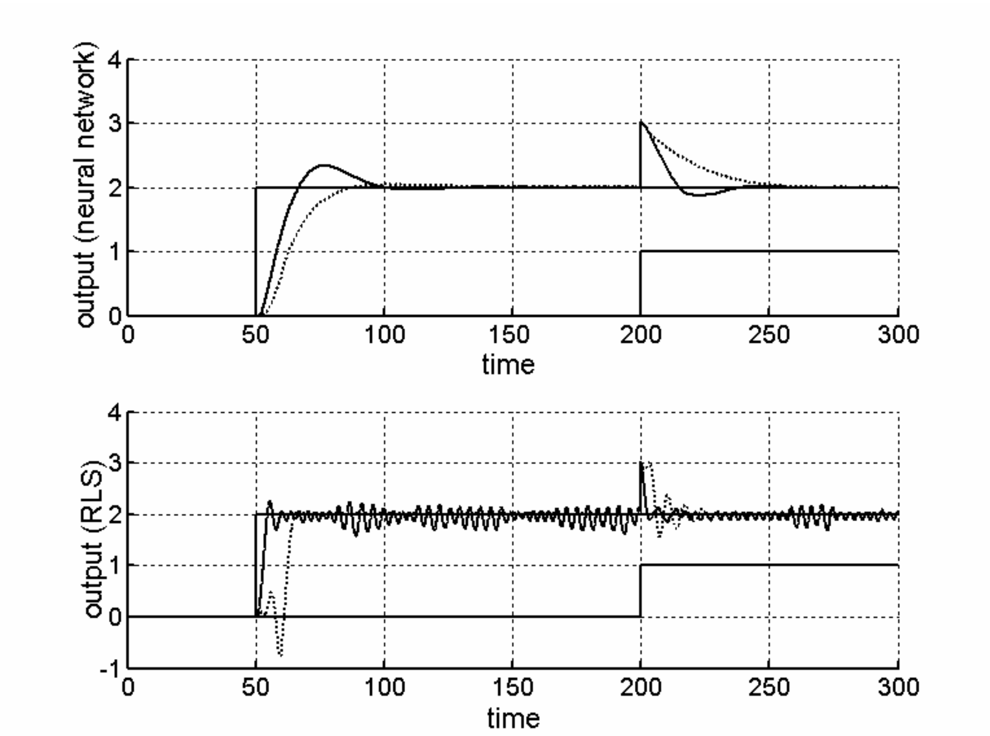

Fig. 3: *Influence of the sampling period ($T_S = 0.1\,s$ -solid lines, $T_S = 0.5\,s$ -dotted lines) by using Takahashi controller with RLS identification (bottom figure) and neural network based identification (upper figure). (Conditions as in **Fig. 2**)*

4 CONCLUSIONS

In this paper there were briefly introduced and compare two different methods of identification suitable for adaptive control. The classical identification algorithm (RLS) was compared with identification based on neural networks, it was used the well-known training algorithm backpropagation. The results were mentioned in previous chapter.

The neural network based identification gives less accurate solution than classical identification but it produces the more stable solution for short sampling periods.

The neural network is for its advantages: the ability to decrease the quantization effect, the better disturbance cancellation, etc. suitable for the real processes.

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