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PROCESS IDENTIFICATION IN SELF-TUNING CONTROLLERS

IDENTIFIKACE PROCESU V SAMOČINNĚ SE NASTAVUJÍCÍCH REGULÁTORECH

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.

Abstrakt

Tento příspěvek se zabývá problémy spojenými s identifikací v adaptivním řízení. Jsou zmíněny klasické rekurzívní identifikační algoritmy a také nový přístup založený na identifikaci pomocí neuronové sítě. Oba přístupy jsou ilustrovány na praktickém příkladě. V příspěvku je také zmíněna neuronová síť pro odhad parametrů lineárního modelu procesu vhodná pro identifikaci reálného procesu.

1 INTRODUCTION

Process identification is the main part of the self-tuning controller, which the controller parameters and thus the controller action depend on. The classical identification methods based on the Least-Mean-Square algorithm are widely extended. Their advantage is fast convergence of the model parameters. But the significant defect of the classical methods is the requirement of a long sample time for the proper identification which can result improper behaviour of the whole control system. The most advantages of the fast sampling are faster disturbances cancellation and smaller overshoots in the control process. Therefore it is appropriate to find new identification methods.

The paper describes one approach – the neural network based on-line identification. Suitability of using the neural network for the model parameter estimation is discussed depending on the ability to face up to quantization effect, noise and disturbance canceling.

The self-tuning controller with on-line model parameter estimation based on the neural network and the self-tuning controller with model parameter estimation using classical identification methods are designed.

2 PROCESS IDENTIFICATION

Adaptive controllers use the process model estimated of actual process inputs and outputs and its parameters are then made use of updating the controller parameters and the controller action. The model and controller parameters are updated in every samp[1]le time T_s .

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

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$$\hat{y}_k = \varphi_k^T \mathbf{\theta}_k \,, \qquad (1)$$

where:

φ_k – regression vector,

$\mathbf{\theta}_k$ – vector of model parameter.

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:

$$\mathbf{\theta}_{k+1} = \mathbf{\theta}_k + \mathbf{K}_{k+1}(y_k - \varphi_k^T \mathbf{\theta}_k) \,, \qquad (2)$$

$$\mathbf{K}_{k+1} = \mathbf{P}_k \varphi_{k+1} \left[\lambda + \varphi_{k+1}^T \mathbf{P}_k \varphi_{k+1}]^{-1} \right], \qquad (3)$$

$$\mathbf{P}_{k+1} = \mathbf{P}_k - \mathbf{K}_{k+1} \varphi_{k+1}^T \mathbf{P}_k \,, \qquad (4)$$

where:

$\mathbf{K}_k$ – vector of correction,

$\mathbf{P}_k$ – covariance matrix,

λ – forgetting factor ($0 < \lambda \le 1$).

Correct behaviour of the RLS algorithm is contingent on the covariance matrix, which must be positive semi-definite in every sample time. When it is ill conditioned the RLS algorithm fails. Solution can be to factorize covariance matrix and thus to use the RLS with LD-FIL decomposition [5].

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 (1).

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

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta_k \cdot \frac{\partial E_k}{\partial \mathbf{w}_k} + \alpha\left(\mathbf{w}_k - \mathbf{w}_{k-1}\right), \qquad (5)$$

where:

$n = \dim(\mathbf{\theta})$,

η_k – learning-rate parameter vector,

α – momentum constant.

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

$$E_k = \frac{1}{2}\sum_{i=1}^{m+n}(\hat{y}_k - y_k)^2 = \frac{1}{2}\sum_{i=1}^{m+n}(\varphi_k^T \boldsymbol{\theta}_k - y_k)^2 \ , \tag{6}$$

These parameters (η_k , α) have an influence on the rate of convergence. The parameters should be limited to interval (0, 1).

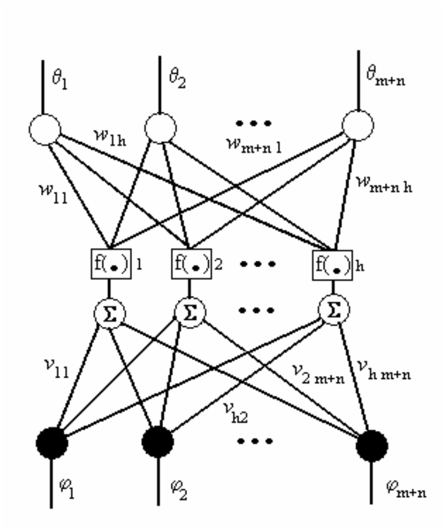

Fig. 1 Neural network usable for parameter estimation of the linear model

3 REAL PROCESS IDENTIFICATION

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.

4 PRACTICAL RESULTS

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

$$F_p(s) = \frac{1}{(s+1)(s+1)(10s+1)}, \tag{9}$$

self-tuning controller was Takahashi controller

$$\begin{aligned} u_k &= K_p(y_{k-1} - y_k) + K_I(w_k - y_k) + K_D(2y_{k-1} - y_{k-2} - y_k) + u_{k-1} \\ K_P &= 0{,}6K_U,\ K_I = \frac{1.2K_U T_s}{T_U},\ K_D = \frac{3K_U T_U}{40T_s} \end{aligned}\ , \tag{10}$$

where:

u_k – control action,

w_k – desired value,

y_k – process output,

K_U – ultimate gain (Z-N method),

T_U – ultimate period (Z-N method),

T_s – sample time.

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.

Note that the neural network based identification gives less accurate solution than classical identification but it produces the most stable solution (the process input and output) for short sampling periods.

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.

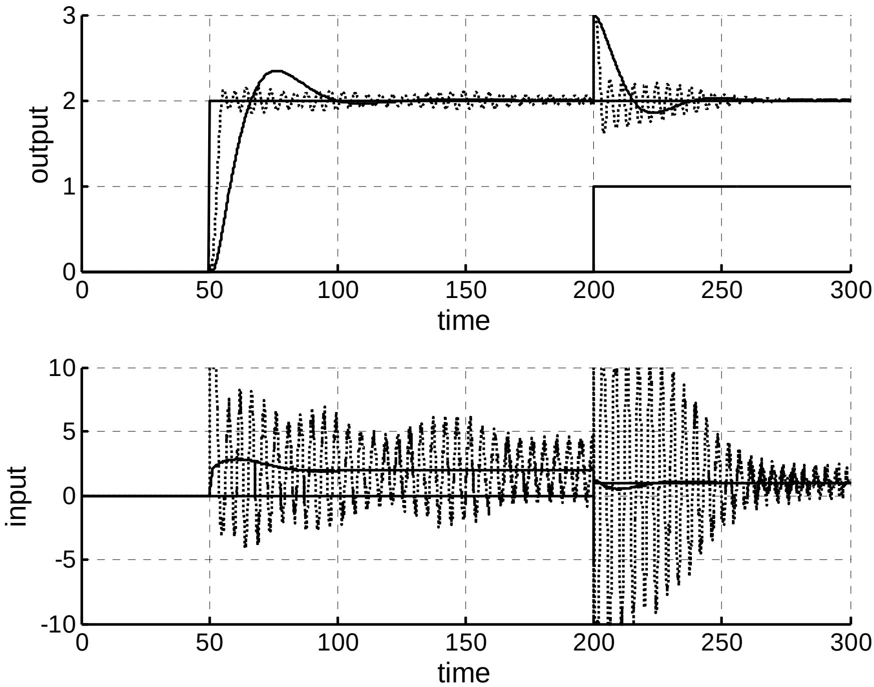

Fig. 2 Takahashi controller with RLS identification (dotted lines) and with neural network based identification - $T_s = 0.1$, $h = 6$, $\eta = 0.002$, $\alpha = 0.1$ (solid lines) using 12 bits A/D and D/A converters. Desired value is set to +2 at time 50 s, at time 200 s disturbance +1 influences

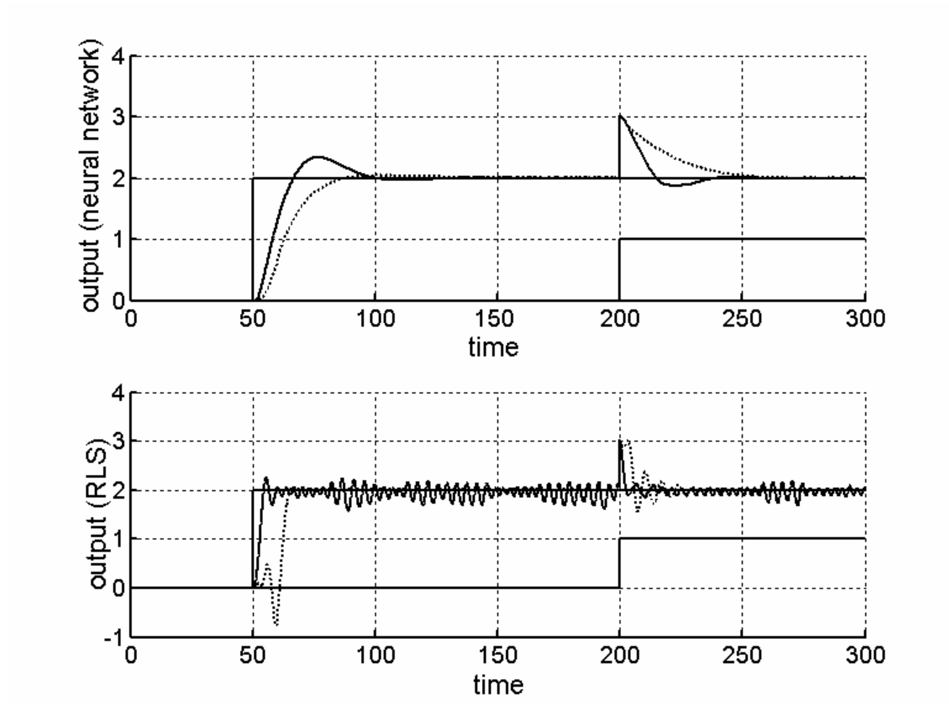

Fig. 3 Influence of the sampling period ($T_s = 0.1\,s$ -solid lines, $T_s = 0.5\,s$ -dotted lines) by using Takahashi controller with RLS identification (bottom figure) and neural network based identification (upper figure). (Conditions as in Fig. 2)

5 CONCLUSIONS

The identification is the most problematic part in the adaptive control. Presumption for the correct adaptive control is a proper function of the identification. The main goal is a suitable choice of the sampling period. The quantization effect in real process can have the significant effect on the control system as well as disturbances, noise and other nonlinearities. Classical recursive identification algorithms can´t deal with them. Hence it was presented the identification based on neural networks.

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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