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Adaptive Controller with Identification Based on Neural Network for Systems with Rapid Sampling Rates

VÁCLAV VELEBA, PETR PIVOŇKA
Department of Control and Instrumentation
Faculty of Electrical Engineering and Communication, Brno University of Technology
Kolejní 4, 612 00 Brno
CZECH REPUBLIC

http://www.uamt.feec.vutbr.cz/rizeni/index.html.en

Abstract: - In this paper ability of three identification methods to parameter estimation of the dynamic plant with great ratio of its time constant to sampling periods is compared. We concentrate our attention on dealing with adverse effects that work on real-time identification of process, especially quantization. It is shown, that a neural network applied to on-line identification process produces more stable solution in the rapid sampling domain. Taking advantage of this result, we propose here an adaptive controller with a neural network as on-line estimator. Simple heuristic synthesis based on modified Ziegler-Nichols open loop method (Z-N 1) are discussed, that deals with bad-estimated model of a plant and gives numerically stable parameters of the PID discrete controller.

Key-Words: - Rapid Sampling, Quantization, Neural Network, Training Set, Levenberg-Marquardt Minimization, Discrete PID Controller, RLS Identification Method

1 Introduction

The correct choice of the sampling period is a top-priority task in adaptive control. It is important to keep in mind, that long sampling period results problem with an aliasing. On the other hands, rapid sampling causes problem with numerical stability. The most advantages of fast sampling are faster disturbances cancellation and smaller overshoots in control process.

When we use the classical identification method with a rapid sampling rate for a real time identification of a real dynamic plant, this method fails. Thought simulation (even with simulated disturbances) behaves differently. This fact is caused by existence of quantization in an A/D converter. The quantization effect, the real noise and other nonlinearities of the plant make on-line identification more complex than could be expected.

We will show that possible solution of this problem is using of an identification method based on neural networks.

2 On-Line Identification

The basic idea of on-line identification is to compare the output of estimated system with the output of model during some time. The model is describable as a parameter vector . The aim is to adjust parameter until the model output is similar to the observed system output. The classical RLS method and gradient method compares only actual model output to system output, while the identification method based on neural network-approaches compares outputs over some interval of time defined by length of training set.

2.1 Linear Regression

The predicted output can be expressed as a linear function of vector $\boldsymbol{\theta}$; that is

$$\hat{y}(k) = \varphi^{\mathrm{T}}(k)\boldsymbol{\theta}(k) \tag{1}$$

where $\varphi(k)$ is vector of measured variables. We use a discrete time shift operator model ARMA expressed in form

$$y(k) = \sum_{i=1}^{m} b_i u(k-i) - \sum_{j=1}^{n} a_j y(k-j) \tag{2}$$

where b_i and a_j are the vector $\boldsymbol{\theta}$ parameters

$$\boldsymbol{\theta}(k) = \left[b_1(k) \quad \cdots \quad b_m(k) \quad a_1(k) \quad \cdots \quad a_n(k)\right]^{\mathrm{T}} \tag{3}$$

In accordance with (1) we write

$$\begin{aligned}\varphi(k) = [&u(k-1) \quad \cdots \quad u(k-1-m) \\ &-y(k-1) \quad \cdots \quad -y(k-1-n)]^{\mathrm{T}}\end{aligned} \tag{4}$$

2.2 Classical RLS Identification

Recursive least mean square identification (RLS) is widely used method. It is often used in case that data comes continuously in time (e.g. on-line estimation). In each sampling period vector $\boldsymbol{\theta}$ is updated by

$$\boldsymbol{\theta}(k+1)=\boldsymbol{\theta}(k)+\boldsymbol{K}(k+1)\left(y(k)-\varphi^{\mathrm{T}}(k)\boldsymbol{\theta}(k)\right) \quad (5)$$

It is interesting to note that the model $\boldsymbol{\theta}(k+1)$ is updated through a prediction error that has vary small value even inaccurate vector $\boldsymbol{\theta}(k)$ is used. This problem cause that RLS is sensitive to disturbances.

The posteriori information of the model errors is incorporated in covariance matrix $\boldsymbol{P}(k)$ that is updated too

$$\boldsymbol{P}(k+1)=\boldsymbol{P}(k)-\boldsymbol{K}(k+1)\varphi^{\mathrm{T}}(k+1)\boldsymbol{P}(k) \quad (6)$$

Vector of correction $\boldsymbol{K}(k+1)$ is computed by applying covariance matrix

$$\boldsymbol{K}(k+1)=\boldsymbol{P}(k)\varphi(k+1)\left[1+\varphi^{\mathrm{T}}(k+1)\boldsymbol{P}(k)\varphi(k+1)\right]^{-1} \quad (7)$$

2.3 Simple Gradient Identification

Simple gradient identification is an older method, which become more popular by expansions of neural network techniques. It is suitable especially for fluently perturbed system identification. It has the worst quality for identification of unknown processes (from described methods), but its advantage is simplicity and small time-consuming computation.

$$\begin{aligned}\boldsymbol{\theta}(k+1)=\boldsymbol{\theta}(k)+\eta(\boldsymbol{\theta}(k)-\boldsymbol{\theta}(k-1))\\ +\mu\left(y(k+1)-\varphi^{\mathrm{T}}(k+1)\boldsymbol{\theta}(k)\right)\varphi\end{aligned} \quad (8)$$

You can note similarly to the RLS method that model is updated by the same principle. That affects the similar problems like the RLS method.

Parameter η in (8) is momentum constant and parameter μ is learning-rate constant.

2.4. Identification Based on Neural Network with Levenberg-Marquardt Training Method

The Levenberg-Marquardt iterative algorithm, gives a numerical solution to the problem of minimizing a sum of squares of generally nonlinear functions.

We can consider a real dynamic system to be nonlinear because it contains nonlinear saturation, A/D (D/A) converters with constrained inputs (outputs) and quantization.

The L-M identification works according to the principle of searching of global minima of an error between the plant last outputs and model outputs through entire a states buffer

$$\boldsymbol{X}(k)=\left[\varphi(k) \quad \varphi(k-1) \quad \ldots \quad \varphi(k-p)\right] \quad (9)$$

The states buffer (training set) contains a certain number of last states of the plant $\varphi(k),\varphi(k-1),\cdots\varphi(k-p)$, where p is a length of buffer. It is desirable to set the length of buffer that the buffer contains a time period invariant to the sampling rate.

The minimization algorithm iterate certain number of iterations i at each identification step k

$$\begin{aligned}\boldsymbol{\theta}(i\,|\,k+1)&=\boldsymbol{\theta}(i\,|\,k)\\ &-\left[\boldsymbol{J}^{\mathrm{T}}(i\,|\,k)\boldsymbol{J}(i\,|\,k)+\alpha\boldsymbol{I}\right]^{-1}\boldsymbol{J}^{\mathrm{T}}(i\,|\,k)\boldsymbol{E}(i\,|\,k)\end{aligned} \quad (10)$$

where $\boldsymbol{E}(i\,|\,k)$ is a vector of errors (11) between model output and estimated system output $\boldsymbol{T}(k)$ (12)

$$\boldsymbol{E}(k)=\boldsymbol{T}^{\mathrm{T}}(k)-\boldsymbol{X}^{\mathrm{T}}(k)\boldsymbol{\theta}(k) \quad (11)$$

$$\boldsymbol{T}(k)=\left[y(k) \quad y(k-1) \quad \ldots \quad y(k-p)\right] \quad (12)$$

The Jacobian matrix $\boldsymbol{J}(i\,|\,k)$ represents the best linear approximation to a differentiable vector-valued function near a given point and is evaluated at each iteration:

$$\boldsymbol{J}(k)=\frac{\partial\boldsymbol{E}(k)}{\partial\boldsymbol{\theta}(k)}=\frac{\partial\left(\boldsymbol{T}^{\mathrm{T}}(k)-\boldsymbol{X}^{\mathrm{T}}(k)\boldsymbol{\theta}(k)\right)}{\partial\boldsymbol{\theta}(k)}=-\boldsymbol{X}^{\mathrm{T}}(k) \quad (13)$$

The (non-negative) damping factor λ is adjusted at each iteration by evaluation of a quadratic control error

2.5 The Influence of Rapid Sampling and Quantization on the Applicability of Identification Methods

In the introduction chapter, we explained that long sampling period causes a loss of information during control process, and this usually results in inferior performance of control process. Long sampling periods hinders especially fast disturbance rejection.

On the other hand, rapid sampling gives problems with a numerical stability of identification algorithms. This effect is more appreciable when a noise occurs. There exists the minimal noise disturbance in the real controlled plant caused by quantization in the A/D and D/A converters. Quantization noise follows a uniform distribution.

We could say that with the raising of relative time constant of a plant, identification process becomes more difficult. The relative time constant is defined

$$T_{\mathrm{REL}}=\frac{T_{\mathrm{G}}}{T_{\mathrm{S}}} \quad (14)$$

where T_{G} is a General time constant of plant ($T_{\mathrm{G}}\approx\sum\text{Time constants of plant}$) and T_{S} is the sampling period.

The influence of sampling period and quantization is shown in Fig. 1, Fig. 2 and Fig. 3. Note that the identification based on a neural network gives less accurate solution, but **it produces the most stable solution in the rapid sampling domain**. This probably arises from an existence of the states buffer.

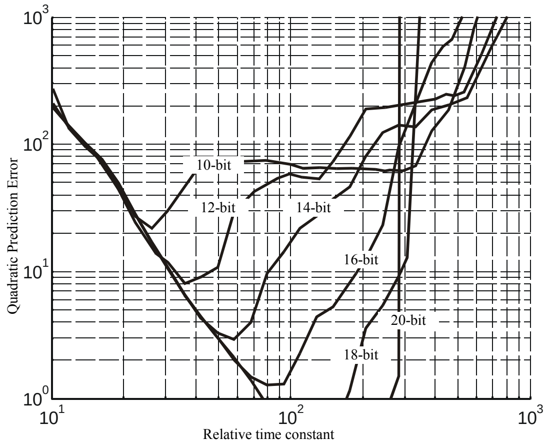

Fig. 1. The influence of sampling period and quantization (from 10-bit to 20-bit converter) on the performance of an identification. RLS algorithm

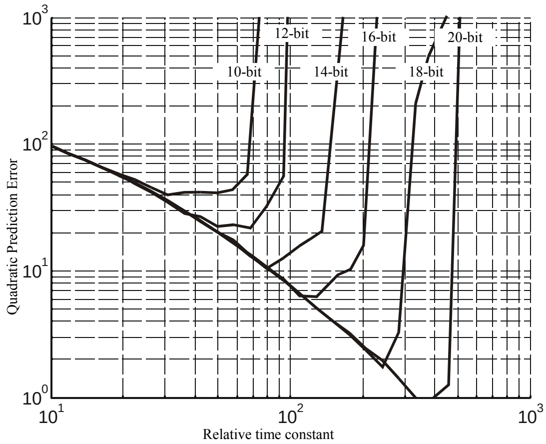

Fig. 2. The influence of sampling period and quantization (from 10-bit to 20-bit converter) on the performance of an identification. Simple Gradient Algorithm

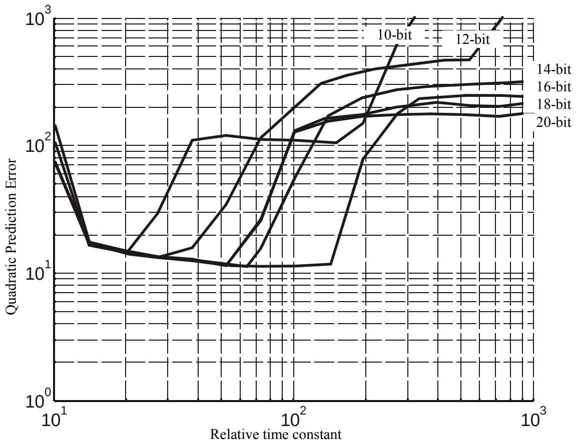

Fig. 3. The influence of sampling period and quantization (from 10-bit to 20-bit converter) on the performance of an identification. Identification based on neural network with Levenberg-Marquardt training method

3 Adaptive Control

Application that on-line parameter identification can be put to is in adaptive control. The idea of adaptive controllers (or self-tuning controllers) is to combine an on-line identification with on-line control law synthesis. Many of control law synthesis approaches are based on two methods – pole placement and inversion of dynamic. Both of the methods are numerically sensitive to the bad-estimated model of a plant. The requirement for correctly computed vector $\boldsymbol{\theta}$ is not often fulfilled during controlling of a real system with a higher order. Therefore, we use simple heuristic synthesis based on modified Z-N 1 method. The basis architecture of the adaptive controller we discussed is shown in Fig. 4 The step response generator generates the sequence Y_{R} of a step response of the estimated model $\boldsymbol{\theta}$. Then, the state machine finds characteristic points $T_{10\%}$, $T_{90\%}$ and $Y_{100\%}$ in the sequence Y_{R} (Fig. 5). These values are used to design the PID discrete controller (15), (16).

$$L = 0.8T_{10\%}\,,\ R = \frac{Y_{100\%}}{T_{90\%} - L} \qquad (15)$$

$$K_{\mathrm{P}} = \frac{0.8}{RL}\,,\ T_{\mathrm{I}} = 3L\,,\ T_{\mathrm{D}} = 0.5L \qquad (16)$$

3.1. Real Process Control Results

The comparison of a controller that uses RLS identification method with a controller that uses identification based on neural network with Levenberg-Marquardt training method is shown. The real process control proves the advantages of the second identification method. The transfer function of controlled dynamic system was

$$F(s) \approx \frac{1}{(10s+1)(s+1)^2} \qquad (15)$$

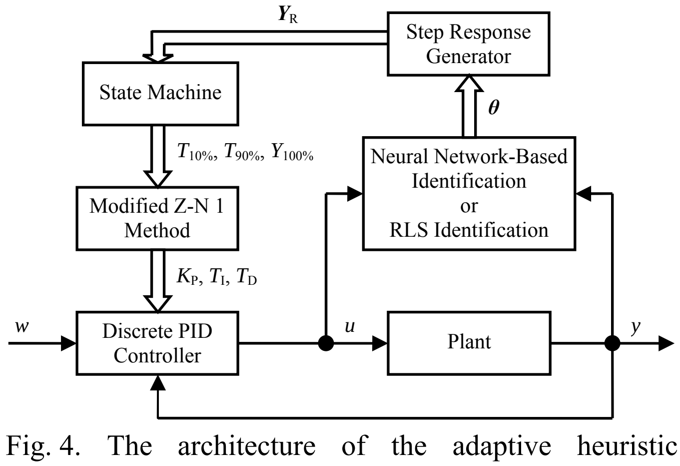

Fig. 4. The architecture of the adaptive heuristic controller based on modified Ziegler-Nichols open loop method

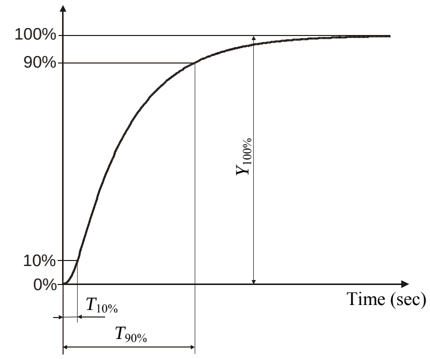

Fig. 5. The characteristic points used for a tuning of the adaptive heuristic controller based on modified Ziegler-Nichols open loop method

with interval of linearity $\langle -6, 7 \rangle$ volts.

Fig. 6 and Fig. 7 shows the both methods of identification applied in an adaptive control. Both controllers work with the same settings. The sampling period was set to $T_S = 0.1$ second. The short sampling period is used in order to reduced an overshot and mainly for a disturbance cancellation.

4 Conclusion

This paper discus influences which affecting process of identification at rapid sampling domain. We compared three methods of on-line identification: the recursive least square method, the gradient identification method and the identification method based on neural network approach with Levenberg-Marquardt minimization. On the basis of chapter 2.5 we applied the neural estimator for an adaptive control.

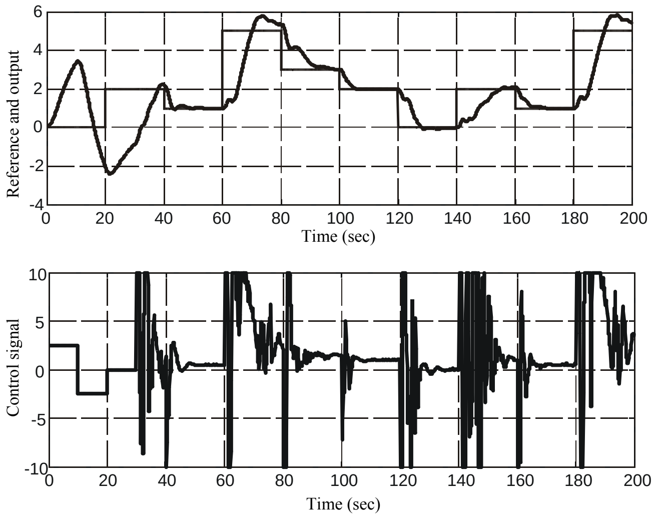

Fig. 6. Real process control – RLS identification method

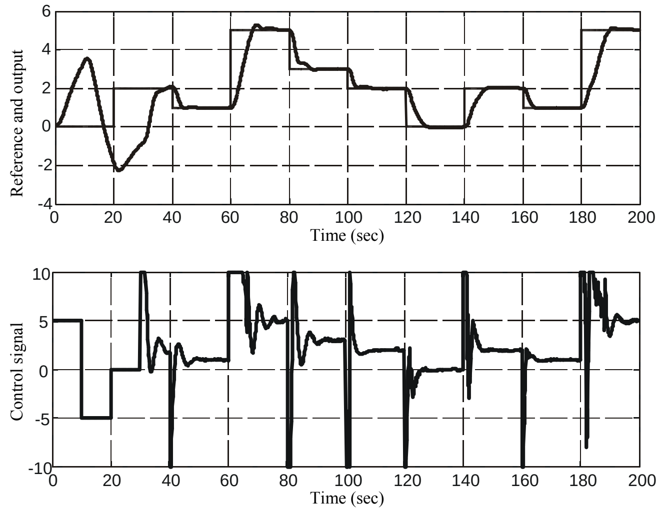

Fig. 7. Real process control – identification method based on neural network

The real process control shows the advantage of using identification based on neural networks in the real application against the classical identification methods. The identification based on a neural network gives less accurate solution, but it produces the most stable solution in the rapid sampling domain.

It was shown that:

- Quantization deeply affects a performance of identification
- Neural networks based identification enables plants with greater T_{REL} to be used in adaptive control process.
- On-line control law synthesis with step response generator provides stable coefficients of discrete PID controller

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References:

[1] Švancara, K., Pivoňka, P.: The Issue of Quantization Effect in Direct Implementation of Adaptive LQ Controller with NN Identification into PLC. *In The 3rd Conference European Society for Fuzzy Logic and Technology*, Zittau, Germany, 2003

[2] Middleton, R., Goodwin G.: *Digital Control and Estimation A Unified Approach,* Prentice-Hall Inc., 1990

[3] Widrow, B., Walach, E.*: Adaptive Inverse Control*, Prentice-Hall Inc., 1996

[4] Cichocki, A., Unbehauen, R.: *Neural Networks for Optimization and Signal Processing*, John Wiley & Sons Ltd., 1994