THE ADVANTAGES OF IDENTIFICATION BASED ON NEURAL NETWORK APPROACH

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ABSTRACT

The parameters estimation of the dynamic plant with great ratio of its time constant to sampling periods is considered. It is shown, that a neural network applied to on-line identification process produces more stable solution in the rapid sampling domain. Considering this results, we apply neural network as on-line estimator in an adaptive controller. Simple heuristic synthesis based on modified Ziegler-Nichols open loop method (Z-N 1) are discussed, that gives numerically stable parameters of the PID discrete controller.

1 INTRODUCTION

The correct choice of the sampling period T_S 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.

2 ON-LINE IDENTIFICATION

The basic idea of on-line identification is to compare the output of estimated system $y(k)$ with the output of model $\hat{y}(\boldsymbol{\theta}, k)$ during some time. The model is describable as a parameter vector $\boldsymbol{\theta}$. The aim is to adjust parameter $\boldsymbol{\theta}$ until the model output $\hat{y}(\boldsymbol{\theta}, k)$ 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 REGRESSOR

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

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

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

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

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

$$\boldsymbol{\theta}(k) = \begin{bmatrix} b_1(k) & \cdots & b_m(k) & a_1(k) & \cdots & a_n(k) \end{bmatrix}^{\mathrm{T}} \qquad (3)$$

In accordance with (1) we write

$$\varphi(k) = \begin{bmatrix} u(k-1) & \cdots & u(k-1-m) & -y(k-1) & \cdots & -y(k-1-n) \end{bmatrix}^{\mathrm{T}} \qquad (4)$$

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

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

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

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

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

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

2.3 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.

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

$$\boldsymbol{X}(k) = \begin{bmatrix} \varphi(k) & \varphi(k-1) & \ldots & \varphi(k-p) \end{bmatrix} \qquad (8)$$

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

$$\boldsymbol{\theta}(i \mid k+1) = \boldsymbol{\theta}(i \mid k) - \left[\boldsymbol{J}(i \mid k)^{\mathrm{T}} \boldsymbol{J}(i \mid k) + \alpha \boldsymbol{I}\right]^{-1} \boldsymbol{J}(i \mid k)^{\mathrm{T}} \boldsymbol{E}(i \mid k) \qquad (9)$$

where $\boldsymbol{E}(i \mid k)$ is a vector of errors (10) between model output and estimated system output $\boldsymbol{T}(k)$ (11).

$$\boldsymbol{E}(k) = \boldsymbol{T}(k)^{\mathrm{T}} - \boldsymbol{X}(k)^{\mathrm{T}} \boldsymbol{\theta}(k), \; \boldsymbol{T}(k) = \left[y(k) \quad y(k-1) \quad \ldots \quad y(k-p)\right] \qquad (10), (11)$$

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

$$\boldsymbol{J}(k) = \frac{\partial \boldsymbol{E}(k)}{\partial \boldsymbol{\theta}(k)} = \frac{\partial\left(\boldsymbol{T}(k)^{\mathrm{T}} - \boldsymbol{X}(k)^{\mathrm{T}} \boldsymbol{\theta}(k)\right)}{\partial \boldsymbol{\theta}(k)} = -\boldsymbol{X}(k)^{\mathrm{T}} \qquad (12)$$

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

2.4 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 normal 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

$$T_{\mathrm{REL}} = \frac{T_{\mathrm{G}}}{T_{\mathrm{S}}} \qquad (13)$$

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 figure 1. Note that the identification based on a neural network gives less accurate solution, but **it produces more stable solution in the rapid sampling domain**. This probably arises from an existence of the states buffer.

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.

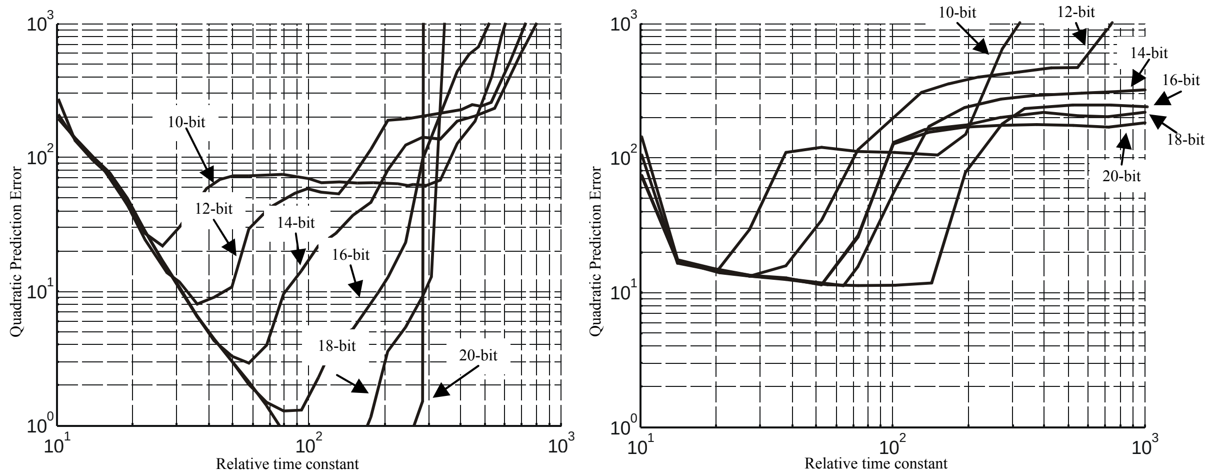

Fig. 1: *Influence of sampling period and quantization (from 10-bit to 20-bit converter) on the performance of an identification. RLS algorithm – on the left; identification based on neural network approach – on the right*

Then, the state machine finds characteristic points $T_{10\%}$, $T_{90\%}$ and $Y_{100\%}$ in the sequence Y_{R} (figure 2 on the right).This values are used to design the PID discrete controller (14).

$$L = 0.8T_{10\%}\,,\; R = \frac{Y_{100\%}}{T_{90\%} - L}\,, K_{\mathrm{P}} = \frac{0.8}{RL}, T_{\mathrm{I}} = 3L\,, T_{\mathrm{D}} = 0.5L \tag{14}$$

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 $F(s) \approx \dfrac{1}{(10s+1)(s+1)^2}$

Figure 3 shows the both methods of identification applied in an adaptive control. Both controllers work with the same settings. The sampling period was set to $T_{\mathrm{S}} = 0.1$ sec.

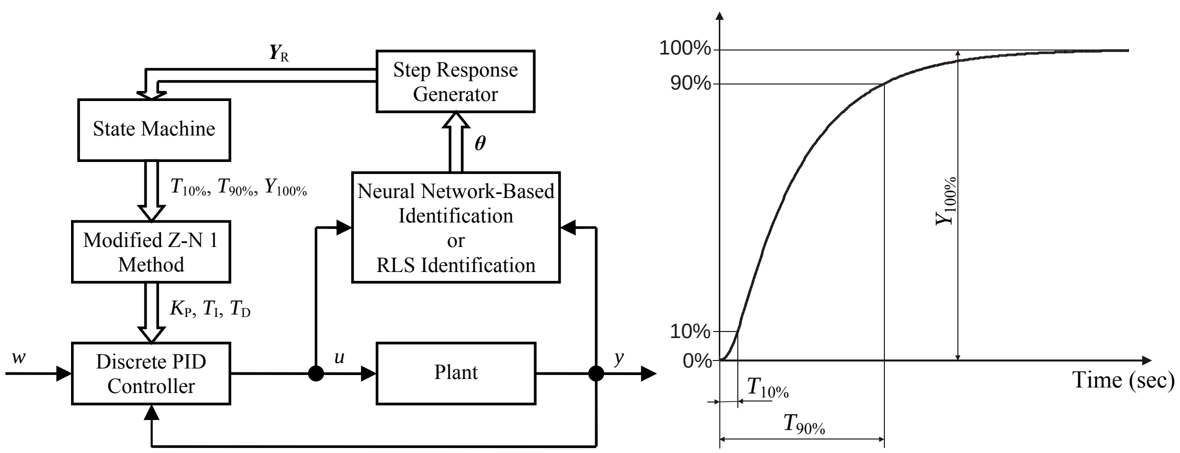

Fig. 2: *The architecture of the adaptive controller –on the left; the characteristic points used for a tuning of controller – on the right*

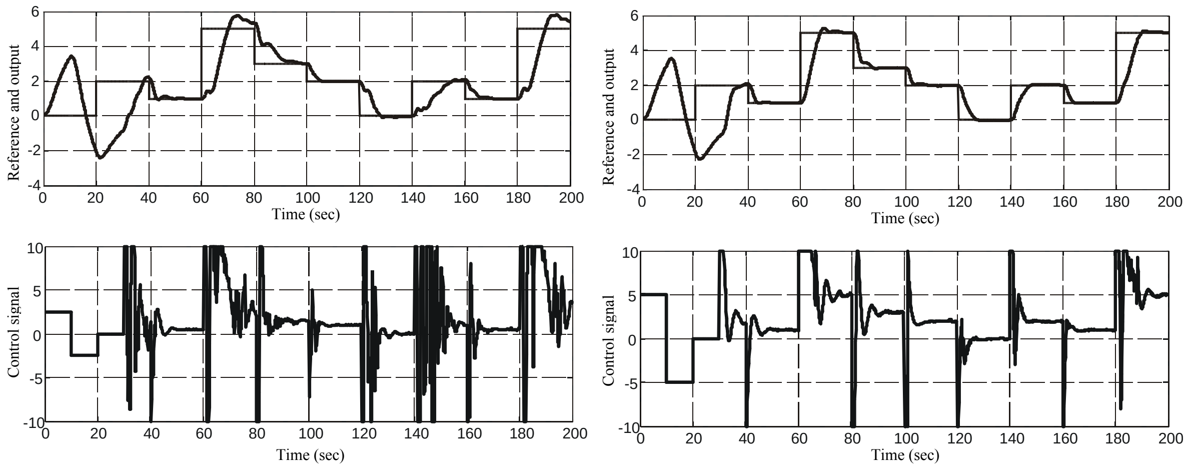

Fig. 3: *Real process control. RLS – on the left; neural network method – on the right*

CONCLUSIONS

This paper discus influences which affecting process of identification at rapid sampling domain. Based on chapter 2.4 we applied the neural estimator for an adaptive control. The real process control shows the advantage of using identification based on neural networks in the real process control against the classical identification methods.

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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