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Adaptive Iterative Methods for Simultaneous Identification and Control

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Abstract: The controller setting is a simple task if the process parameters are known. If the process model is not known then the modern approach is the adaptive method. The paper shows that the complex problem of the adaptive iterative methods for simultaneous identification and control how can be handled.

Keywords: Adaptive, iterative, simultaneous, control identification.

1. INTRODUCTION

It is a general problem of control systems design how to solve the combined application of process identification (ID) and controller design. In a real technological environment, open-loop measurements are generally not welcome, so the classical method of open-loop ID can be applied very rarely. It is mostly used in laboratory tests or processes when the improper operation has no high risk or costs.

It can be generally stated that the better the process model, the better the control design. Therefore it is a continuous requirement to improve the quality of the model obtained from the ID. It can be done by repeated measurement (experiments). The techniques where the new measurements are used to renew the model structure and parameter estimation in each sampling are called learning or adaptive methods referring both to the renewal of the process model and to the redesign of the controller.

It is also known that the accuracy of the obtained model strongly depends on the applied excitation, which – in case of a closed-loop experiment – can only be reached by the optimization of the reference signal (Keviczky and Bányász (2015)).

In the control engineering practice it is also known that the reachable best control can be reached by taking the available actuator amplitude constraint into consideration (Ljung (1999), Maciejowski (1989)).

So the evolving solution of each elements of the above complex methodology is necessary if we want to reach a good control in the practice.

2. THE EVOLVING SOLUTION OF A COMBINED IDENTIFICATION AND CONTROL TASK

The evolving solution of a *simultaneous identification and control* strategy can be performed by iterative methods processing long measurement records (N samples) usually by off-line (*batch*) identification technique and the control is based on the result of the ID. The individual tasks must be solved in this complex problem are the following:

- Optimization of the applied reference signal series. (Because the optimal solution depends on the obtained process model structure and parameters, only an evolving iterative solution can be applied, which is the solution of this "catch of 22".)

- Optimization of the model accuracy: best parameter and structure estimation method have to be applied. (The solution of this task is historically an evolving iterative procedure, which gradually improves the accuracy of the obtained models.) Such ID method is necessary which works well in a closed-loop environment and does not require to open the control loop.

- Optimization of the control design: selecting the best, still applicable control reference models. (Because the optimal reference model depends on the amplitude constraints of the actuator, therefore only an evolving iterative reference model redesign solution can be applied.) The computation of the optimal parameters of a selected controller class is usually a single step solution, if all the necessary information is already available.

In the next, off-line experiment providing the most accurate process model is obviously used. With this technique the optimality of the controller can be gradually improved as the model becomes more and more accurate, while the normal operation of the system is only slightly disturbed. The algorithms of the simultaneous identification and control apply the *KB* parameterization-based (Keviczky and Bányász (2015)) closed-loop ID (Keviczky and Bányász (2001)).

3. THE FORMAL DESCRIPTION OF THE EVOLVING ITERATIVE ALGORITHM

Before the iteration the model class $\mathcal{M}$ (e.g., linear dynamic n-order processes), and the ID criterion $J_{\mathrm{ID}}\left(\varepsilon_{\mathrm{ID}}\right)$ (e.g., *LS*

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method (Ljung (1999))) is chosen. Here ε_{ID} is the modeling error. Similarly, the control class (type) $\mathcal{C}$ and the control criterion $J_{\text{C}}\left(e_{\text{C}}\right)$ (e.g., optimization by the $\mathcal{H}_2$ norm) are also chosen. Here e_{C} is the control error. The coherent order of the steps to be taken in the i-th iteration is:

1. Based on the obtained last best $\hat{G}_{i-1}$ estimation of the process model the input excitation series can be optimized by a selected optimal input design method (Keviczky and Banyasz (2001). Choose the design method $\mathcal{D}$, according to which

$$\mathcal{Y}_r^{i+1} = \mathcal{D}\left\{\mathcal{M}, \hat{G}_i, Y_{\text{r}}^{\text{Max}}\right\} \tag{1}$$

Here $Y_{\text{r}}^{\text{Max}}$ is the biggest amplitude admissible for the reference signal. Then the obtained optimal the series $\mathcal{Y}_r^i = \left\{y_r^i\left[k\right]; k = 1,\ldots,N\right\}$ of the reference signal y_{r} is applied to the input of the closed system.

2. The a priori process model $\hat{G}_{i-1}$ is also used for the computation of the optimal controller by solving the optimality task (see Fig.1)

$$\begin{aligned}\hat{C}_i &= \arg\min_{\hat{C}_i \in \mathsf{C}} J_{\text{ID}}\left(e_{\text{C}}^i\right) = \arg\min_{\hat{C}_i \in \mathsf{C}} J_{\text{ID}}\left[\tilde{e}\left(e_{\text{C}}^i\right), \hat{G}_{i-1}\right] = \\ &= \hat{C}_{\text{opt}}\left(\mathsf{C}, \hat{G}_{i-1}\right)\end{aligned} \tag{2}$$

3. With knowledge of the new controller $\hat{C}_i$ and the reference signal, the actual value of the actuating signal series $\hat{\tilde{u}}_i$ is determined. If the output of the controller violates the available amplitude constraint $u^i = \left\{u^i\left[k\right]; k = 1,\ldots,N\right\} \in U^{\text{Max}}$, then the reference model used in the optimization task (2) must be redesign, i.e., we have to give up some of our original design goals and must use less demanding quality requirements. With the new reference model a "sub-iteration" must be performed going back to point 2.

4. N data pairs $\mho^i = \left\{\hat{u}^i\left[k\right], y^i\left[k\right]; k = 1,\ldots,N\right\}$ are collected if the actuator is accptable and the closed-loop can be operated.

5. Then the estimation of the process parameters, i.e., the ID of the process is performed from the measured data. This step can be formally described by the following expression (see Fig.1)

$$\begin{aligned}\hat{G}_i &= \arg\min_{\hat{G}_i \in \mathcal{M}} J_{\text{ID}}\left(\varepsilon_{\text{ID}}^i\right) = \arg\min_{\hat{G}_i \in \mathcal{M}} J_{\text{ID}}\left(\varepsilon_{\text{ID}}^i\right)\Big|_{\mho^i} = \\ &= \hat{G}\left(\mho^i, \mathcal{M}, G\right)\end{aligned} \tag{3}$$

6. In this step the merit of the obtained model and its distance from the model obtained in the previous iteration is investigated: if the model is acceptable, or the distance is correspondingly small, then the iteration is stopped; otherwise the successive improvement of the model and controller is continued, going back to the first step of this scheme.

The block scheme of the iterative simultaneous identification and control discussed in the above steps is presented in Fig. 1 in the i-th iteration step. It is important to note that the signal $\hat{\tilde{u}}_i$ needs to be determined by using the a priori model $\hat{G}_{i-1}$ and the computation of $\hat{K}_{\text{r}}^{i-1}$.

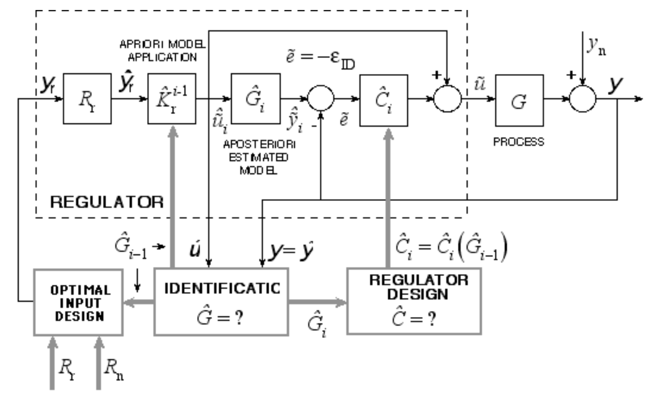

Figure 1. Block scheme of iterative joint identification and control in closed-loop

4. SIMPLE SIMULATION EXAMPLE FOR THE EVOLVING ALGORITHM

The algorithms of the simultaneous identification and control have been tested via several simulation examples. Some of these are shown below.

Example 1.

Let the process be a first-order time-delay system, whose pulse transfer function is

$$G = \frac{0.007869z^{-1}}{1-0.606531z^{-1}}z^{-3} = \frac{0.007869}{1-0.606531z^{-1}}z^{-4} \tag{4}$$

This form represents the effect of the rod control of a helicopter on the sideslip angle. Here the sampling time $T_{\text{s}} = 0.05$ [sec] is applied and the time-delay of the process is $d = 3$. Combined iterative identification and control tests are performed. The reference models with unity gain

$$R_{\text{r}} = \frac{0.5z^{-1}}{1-0.5z^{-1}} \quad \text{and} \quad R_{\text{n}} = \frac{0.2z^{-1}}{1-0.8z^{-1}} \tag{5}$$

are used in the design. The iteration starts with the model

$$\hat{G}_{\text{o}} = \frac{0.01z^{-1}}{1-0.4z^{-1}} \tag{6}$$

A square signal with periodic time of 40 samples times is applied as reference signal. In the simulation it is assumed that the additive noise y_{n} is white noise, whose variance is very small, i.e., $\sigma_{y_{\text{n}}} = 0.01$. In each step $N = 100$ samples are processed. Because of the small output noise a simple off-line *LS* method is used for the identification. The controller is designed by the *YP (YOULA parameterization)* method (Keviczky and Bányász (2015), Keviczky and Bányász (2001), Youla et.al (1974)) assuming an *IS* process.

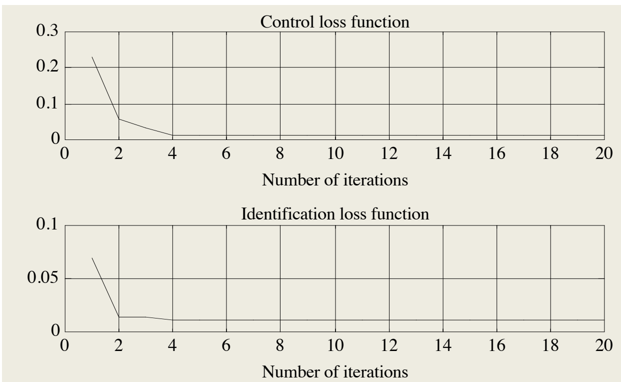

Figure 2. Plot of the loss functions during the iteration (first-order example)

The shape of the identification and control loss functions (variances) during the iteration is shown in Fig. 2. It is evident that the iteration is very fast and reaches the optimal value in four steps. Figure 3 shows the shape of the reference model R_r (continuous line) and the process output (dashed line) at the beginning and end of the iteration.

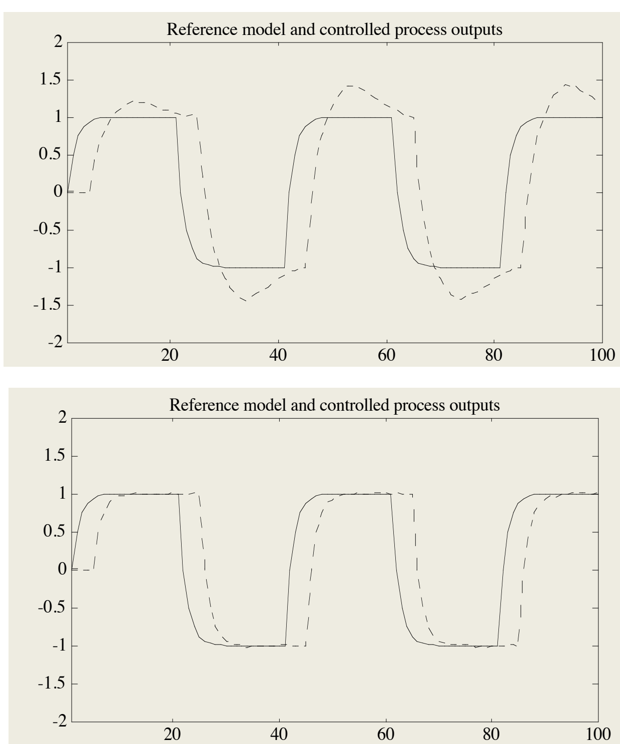

Figure 3. Plot of the reference model R_r and the process output at the beginning and the end of the iteration

The shape of the identification and control loss functions (variances) during the iteration is shown in Fig. 2. It is evident that the iteration is very fast and reaches the optimal value in four steps. Figure 3 shows the shape of the reference model R_r (continuous line) and the process output (dashed line) at the beginning and end of the iteration.

5. OPTIMIZATION OF THE REFERENCE SIGNAL

In many practical cases the identification of the process model should be performed without opening the closed-loop. Several methods exist, but here a method is discussed which uses the advantages and special features of *KB* parameterization (it virtually opens the closed-loop). According to this method the identification is performed between the internal virtual input $\hat{u}$ and the output y of the closed-loop. Besides the favorable prediction features (Keviczky and Bányász (2015), Ljung (1999)) the problem of the *circulating noise* can be avoided by this method. The strange thing about this method is that the value (absolute value) of the control error e is equal to the identification error $\varepsilon_{\mathrm{ID}} = \varepsilon_{\mathrm{KB}}$. For DT (*discrete-time*) system

$$\begin{aligned}\varepsilon_{\mathrm{ID}} &= \varepsilon_{\mathrm{KB}} = -e = y - y_{\mathrm{m}} = y - \hat{G}\hat{u} \approx \\ &\approx \left(R_{\mathrm{r}} G_{\mathrm{r}} \hat{G}\_ z^{-d_{\mathrm{m}}}\right)\left(1 - R_{\mathrm{n}} G_{\mathrm{n}} \hat{G}\_ z^{-d_{\mathrm{m}}}\right) \ell y_{\mathrm{r}} = H_{\mathrm{KB}} \ell y_{\mathrm{r}}\end{aligned} \tag{7}$$

where $d_{\mathrm{m}} \neq d$ is the time-delay of the model. A further fact is that in the case of $\ell \to 0$ the

The optimal reference signal series $\left\{y_{\mathrm{r}}^{\circledast}\left[k\right]; k = 1, \ldots, N\right\}$ is generated by a maximum variance strategy:

$$\begin{aligned}y_{\mathrm{r}}^{\circledast}\left[k\right] &= -\mathrm{sign}\left[y_{\mathrm{r}}^{*}\right] = -\mathrm{sign}\left[-\frac{\boldsymbol{g}^{\mathrm{T}}\left[k-1\right]\boldsymbol{q}}{g_0}\right]; \\ y_{\mathrm{r}}^{*} &= -\frac{\boldsymbol{g}^{\mathrm{T}}\left[k-1\right]\boldsymbol{q}}{g_0}\end{aligned} \tag{8}$$

where

$$\begin{aligned}v\left[k\right] &= H_{\mathrm{KB}} y_{\mathrm{r}}\left[k\right] = \\ &= \left(1 - R_{\mathrm{n}} G_{\mathrm{n}} \hat{P}\_ z^{-d_{\mathrm{m}}}\right) R_{\mathrm{r}} G_{\mathrm{r}} \hat{P}\_ z^{-d_{\mathrm{m}}} y_{\mathrm{r}}\left[k\right] = \\ &= \frac{g_0 + \tilde{\mathcal{G}}\left(z^{-1}\right)}{1 + \tilde{\mathcal{D}}\left(z^{-1}\right)} z^{-d_{\mathrm{m}}} y_{\mathrm{r}}\left[k\right]\end{aligned} \tag{9}$$

It can be rewritten into a difference equation linear in parameters as

$$\begin{aligned}v\left[k + d_{\mathrm{m}}\right] &= g_0 y_{\mathrm{r}}\left(k\right) + \tilde{\mathcal{G}}\left(z^{-1}\right) y_{\mathrm{r}}\left(k-1\right) + \\ &\quad + \tilde{\mathcal{D}}\left(z^{-1}\right) v\left[k + d_{\mathrm{m}} - 1\right] = \\ &= g_0 y_{\mathrm{r}}\left[k\right] + \boldsymbol{g}^{\mathrm{T}}\left[k-1\right]\boldsymbol{q} = g_0 y_{\mathrm{r}}\left[k\right] + b\end{aligned} \tag{10}$$

Here

$$\begin{aligned}\boldsymbol{q} &= \left[g_0, g_1, \ldots; d_1, d_2, \ldots\right]^{\mathrm{T}} \\ \boldsymbol{g}\left[k-1\right] &= \left[y_{\mathrm{r}}\left[k-1\right], \ldots; -v\left[k + d_{\mathrm{m}} - 1\right], \ldots\right]^{\mathrm{T}}\end{aligned} \tag{11}$$

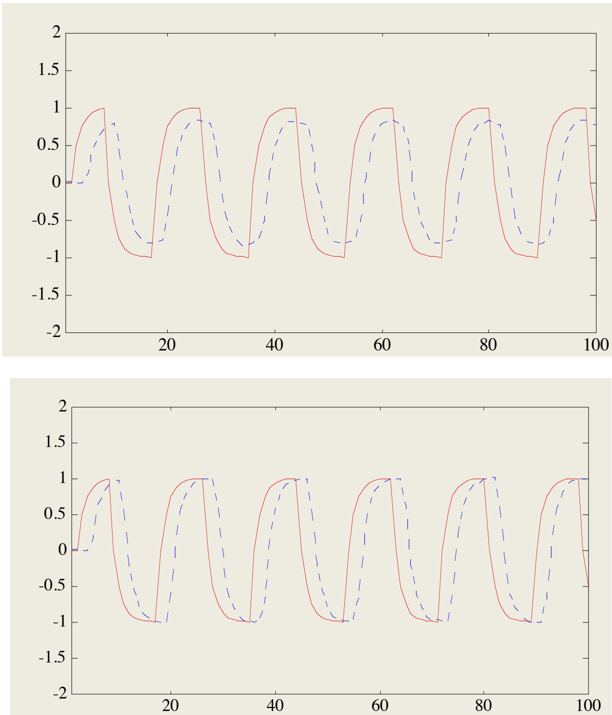

Figure 4. Plot of the reference model R_{r} and the process output at the beginning and the end of the iteration (using optimal reference signal $y_{\mathrm{r}}^{\circledast}[k]$)

Example 2.

Let the process be a second-order one whose pulse transfer function is

$$G=\frac{0.125z^{-1}\left(1+1.6z^{-1}\right)}{\left(1-0.5z^{-1}\right)\left(1-0.8z^{-1}\right)} \tag{12}$$

The same reference models are applied as in the previous examples. Let the output noise be $\sigma_{y_{\mathrm{n}}}=0.01$. The ID is performed by an off-line *LS* method. The number of the processed samples is also the same. The controller is designed by the *YP* method Keviczky and Bányász (2001), Youla et.al (1974) assuming an *IU* process. Let the model be

$$\hat{G}_{\mathrm{o}}=\frac{0.1z^{-1}\left(1+4.0z^{-1}\right)}{\left(1-0.2z^{-1}\right)\left(1-0.9z^{-1}\right)} \tag{13}$$

The reference model R_{r} (continuous line) and the process output (dashed line) are shown in Fig. 4 at the beginning and end of the iteration. Figure 5 shows the amplitude characteristic of the input-generating filter $H_{\mathrm{KB}}(j\omega)$ (continuous line) and the frequency characteristic of the optimal signal $y_{\mathrm{r}}^{\circledast}[k]$ at the end of the iteration. The maximum of $H_{\mathrm{KB}}(j\omega)$ is in the vicinity of the cut-off frequency and it is evident that the signal $y_{\mathrm{r}}^{\circledast}[k]$ concentrates the maximal components in this region.

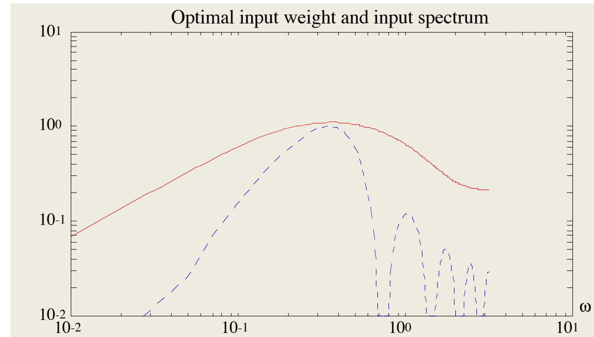

Figure 5. Spectra of the frequency function $\left|H_{\mathrm{KB}}(j\omega)\right|$ (solid line) and the obtained optimal input (dotted line)

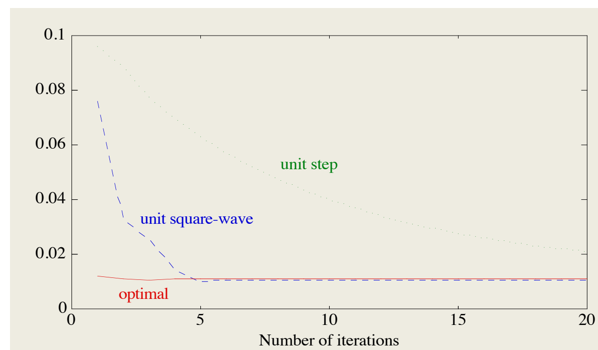

Figure 6. Loss function of the control for different exciting signals

Figure 6 shows the effect of the optimization of the exciting signal, where three input signals are compared: a unit step (dotted), an arbitrary chosen square signal (PRBS) (dashed) and a signal (continuous) optimized by (10). The control loss function is also presented in the figure. It is clear that none of the signals can compete with the optimal excitation in terms of the speed of the iteration. The reason is that the optimal signal provides increasingly accurate model in each step in the vicinity of the frequency region what is important from the controller design perspective.

6. REDESIGN OF THE REFERENCE MODEL

This is perhaps the best place to discuss the redesign algorithm of the reference model. The redesign requires that in the i-th step the coefficient $\hat{f}_{\mathrm{r},1}^{i}$ of the reference model $\hat{R}_{\mathrm{r}}^{i}$ is computed by the coefficient $\hat{g}_1^{i-1}$ of the model $\hat{G}_{i-1}$ obtained by identification in the $[i-1]$-th iteration step, i.e.,

$$\hat{f}_{\mathrm{r},1}^{i}\leq\hat{g}_1^{i-1}U_{\max}-1 \tag{14}$$

The new reference model is obtained as

$$\hat{R}_{\mathrm{r}}^{i}=\frac{\left(1+\hat{f}_{\mathrm{r},1}^{i}\right)z^{-1}}{1+\hat{f}_{\mathrm{r},1}^{i}z^{-1}} \tag{15}$$

Then the strategy of the iterative methods detailed above is continued in the closed-loop. The block scheme of the iterative simultaneous ID and control discussed above is shown in Fig. 7 with the redesign of the reference model in the i-th iteration step.

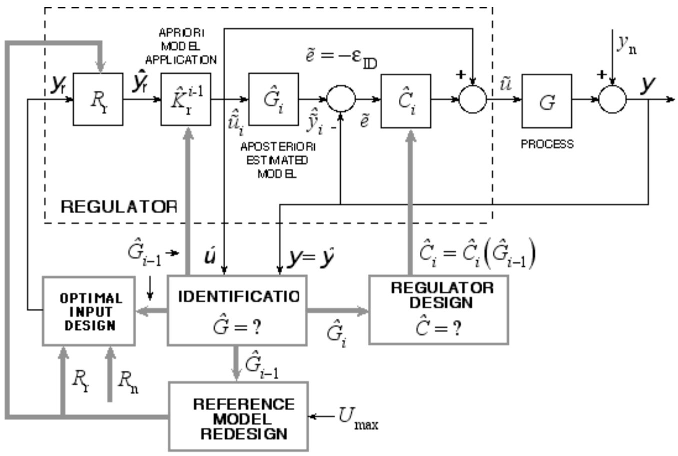

Figure 7. Block scheme of the iterative simultaneous identification and control in closed-loop with redesign of the reference model

The typical response of the classical *PID* controller can be seen in Fig. 8 for square-wave reference signal disturbance.

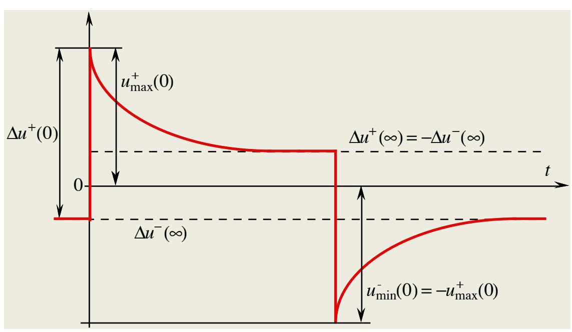

Figure 8. Typical response of the classical *PID* controller in the case of a square-wave disturbance signal

The same kind of transient can be expected at the output of the *YP* controller if $y_r[k]$ has a square signal form. Using the notations of the figure the over-excitation is obtained as

$$u_t = \frac{\Delta u^+(0)}{\Delta u^+(\infty) - \Delta u^-(\infty)} = \frac{\Delta u^+(\infty)}{2\Delta u^+(\infty)} = = \frac{u_{max}^+(0) + \Delta u^+(\infty)}{2\Delta u^+(\infty)} \tag{16}$$

Example 3.

Let the process be given by the pulse transfer function used in Example 2. Combined iterative identification and control tests are performed. The following reference models of unity gain are used for the design

$$R_r = \frac{0.9z^{-1}}{1-0.1z^{-1}} \text{ and } R_n = \frac{0.2z^{-1}}{1-0.8z^{-1}} \tag{17}$$

At the start of the iteration the model

$$\hat{G}_o = \frac{0.1z^{-1}\left(1+4.0z^{-1}\right)}{\left(1-0.2z^{-1}\right)\left(1-0.9z^{-1}\right)} \tag{18}$$

is assumed. A square signal with periodic time of 40 samples is applied as reference signal. In the simulation it is assumed that the additive noise y_n is white noise, whose variance is $\sigma_{y_n} = 0.01$. The number of the processed samples is $N = 100$. Because of the small output noise the identification is performed by a simple off-line *LS* method. The controller is designed by the *YP* method, assuming an *IU* process.

The output of the controller is presented in Fig. 9 where it is seen that the over-excitation is very high at 900 %, i.e., $u_t = 9$. Assume that the actuator can realize only $\bar{u}_t = 5$. This requires the redesign of the reference model R_r.

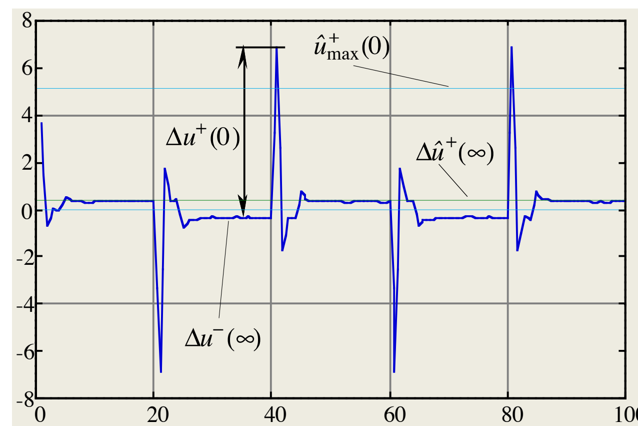

Figure 9. Response of the *YP* controller before the iteration

The output of the controller is shown in Fig. 10 after the iteration.

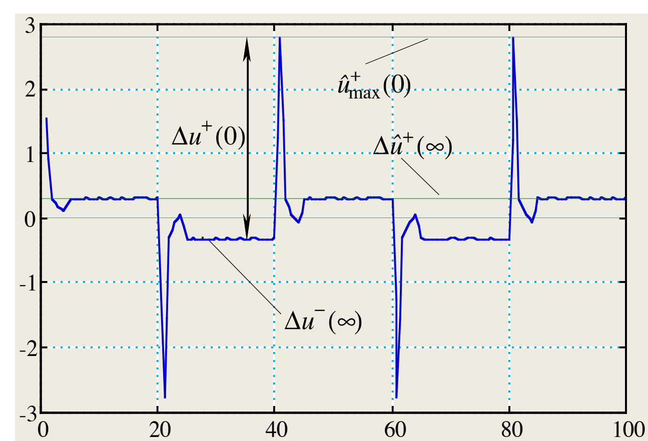

Figure 10. Response of the *YP* controller after the iteration

7. CONCLUSIONS

Our paper presented an evolving complex procedure how the iterative and sub-iterative algorithms can be performed to solve the simultaneous identification and control tasks.

Optimization of the identification purpose reference signal of a closed-loop control system, the optimal reference model based design of the controller itself, the reiterative optimization of the reachable best reference model for the design, the optimization of the process model identification in a special closed-loop ID scheme are involved in this framework.

Some simple computer simulations are presented to demonstrate the effectiveness of this kind of evolving learning procedures.

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