ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 6, Issue 3, March 2019

# Algorithms for Recurrent Identification of Control Objects by Means of Multiple Models and Adaptation of Parameters

**Zaripov Oripjon Olimovich, Shukurova Oysara Pulatovna, Sevinov Jasur Usmonovich**

Professor, Department of of Information processing and control systems, Faculty Electronic and Automatic, Tashkent State Technical University,
Scientific adviser, Department of Information processing and control systems, Tashkent State Technical University, Tashkent, Uzbekistan
Professor, Department of of Information processing and control systems, Faculty Electronic and Automatic, Tashkent State Technical University,

**ABSTRACT**: The results of the formalization of the procedure for constructing a recurrent identification of control objects as a process in a closed dynamic system are presented. It is shown that one of the factors narrowing the scope of application of the identification approach to the tasks of adaptive management is the accuracy requirement of parameter estimates issued by the identifier. To solve the problem under consideration, an approach based on the use of approximation in the form of a finite sum of Gaussian distributions is used. The presented recurrent identification algorithms using multiple models and adapting their parameters based on the use of approximations in the form of a finite sum of Gaussian distributions result in consistent estimates and improve the quality of control processes in closed-loop control systems.

**KEY WORDS**: Control object, recurrent identification, multiple models, parameter adaptation.

## I. INTRODUCTION

Unsteady conditions of operation of industrial facilities make it necessary to constantly monitor changes in the characteristics of external and internal properties of objects when solving research and management problems. To date, a fairly large number of works are known on the operational identification of object models and adaptive management based on such models [1-10].

When designing the software for a specific automatic or automated process control system, two major problems arise [11–13]. The first is the selection and implementation of a relatively simple method for the synthesis of control algorithms with feedback. Algorithms must have a minimal complexity of their implementation on control computers and must provide a sufficiently effective in terms of accuracy and speed in managing objects in real time. The second problem is the selection and implementation in control computers of efficient algorithms for restructuring the structure and parameters of the object model, i.e., identification algorithms. Integration in one system and control with feedback, and the identification process has revived a new class of control systems, called adaptive systems with identifiers (ASI) [11]. The inclusion of an identifier in the feedback circuit leads to the fact that identification occurs in a closed control loop in real time and the main goal of identification is aimed at achieving the control goal.

The implementation of ASI allows for sufficiently effective management of little-studied objects for which neither the structure nor the parameters of their models were known. In the process of ASI implementation, it turned out that the same ASI operation algorithms can be applied to a wide class of objects of different nature. This circumstance allows us to pose the problem of computer-aided design of ASI software. The synthesis of control algorithms with feedback and identification algorithms has a significant impact on this process.

The basis of adaptive dynamic identification and control systems are open dynamic integrated systems of models of the form [14–16]:

$$\begin{cases} Y_t^* = F_0(t, Y_{t-\tau}^*, X_t^*, U_t^*, \xi_t), \\ \overline{V}_{jt} = \overline{F}_j(t, \overline{V}_{j(t-k)}, Z_{jt}, \eta_{jt}), \; j = \overline{1,m}; t, \tau, k = 1,2,3,\ldots, \end{cases} \tag{1}$$

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 6, Issue 3, March 2019

where $Y_t^*, Y_{t-\tau}^*, X_t^*, U_t^*$ – realizations of output $Y$ and input $U$, $X$ controlled and unmanaged variables of the control object; $\bar{V}_{jt}, \bar{V}_{j(t-k)}$ – realization of output variable models of objects of analogues representing additional a priori data, expert estimates of environmental factors, their predicted values and then; $F, \bar{F}_j$ – dynamic models of the object under study and an analogue object, combining models of the state of the control object, initial and boundary conditions, as well as measurement models; $\xi_t, \eta_t$ – random processes representing the errors of the source data, errors of additional a priori information. The variable $Z_j$ analog objects can correspond to the variables of the control object, as well as represent parameters and functions.

Designing adaptive dynamic identification and control systems in terms of uncertainty from the point of view of the systems approach can be represented as the process of choosing the optimal system of alternatives [14,16], which consists in forming initial data, additional a priori information, expert assessments, dynamic system of type models (1), its vector quality indicator, and solving optimization problems. So, for example, with the parametric representation of the control object $Y_t^* = f_0(t, \alpha, Y_{t-\tau}^*, X_t^*, U_t^*, \xi_t)$ and the models of the analog objects $\bar{V}_{jt} = \bar{f}_j(t, \beta, \bar{V}_{j(t-k)}, Z_{jt}, \eta_{jt})$, up to unknown parameters $\alpha$ , $\beta$ , the procedure for choosing the optimal system of alternatives $Z_t(m) = \left\{\alpha, U_t, f_0, \left(\bar{f} = \bar{f}_j, j = \overline{1,m}\right), \beta\right\}$ is reduced to solving optimization control problems with identification:

$$\begin{cases} \alpha_t^*(h_t, \beta_t), f_0^*, \bar{f}^* = \arg\min\limits_{\alpha_t, f_0, \bar{f}} \Phi_1\left(\alpha_t, f_0, \bar{f}, h_t, \beta_t\right), h_t^*, \beta_t^* = \arg\min\limits_{\alpha_t, \beta_t} J_0\left(\alpha_t^*, f_0^*, \bar{f}^*, h_t, \beta_t\right), \\ U_t^* = \arg\min\limits_{U_t} \Phi_2\left(U_t, \alpha_t^*, f_0^*, \bar{f}^*, h_t^*, \beta_t^*\right) \end{cases} \tag{2}$$

Here $Z_t^*(m) = \left(\alpha_t^*, U_t^*, f_0^*, \bar{f}^*, h_t^*, \beta_t^*\right)$ - the best system of alternatives of complexity $m$; $\Phi_1$, $\Phi_2$ – empirical quality functionals consisting of the quality indicator of the control object model $J_0$ and the quality indicators of the object models analogs $\bar{J}_k, k = \overline{1,m}$; $h_t = (h_{1t}, h_{2t}, \ldots, h_{mt})$ – the vector of control parameters determining the significance (weight) of additional a priori data $\bar{V}_{jt}, \bar{V}_{j(t-k)}$, $j = \overline{1,m}$.

The given information integration technology within the framework of the system of models (1) and the optimization of solutions of the form (2), by analogy with [16], allows synthesizing a wide range of new adaptive dynamic identification and control algorithms in conditions of uncertainty with self-organization elements for linear, nonlinear and non-parametric dynamic control objects.

As it is known [1,4-6,17], control algorithms with parameter adaptation provide high quality process control when certain preconditions of stability and convergence are fulfilled. If these conditions are violated, it becomes necessary to introduce a third level of control into the system, which should detect violations of preliminary conditions and carry out parrying effects. The controlling level analyzes and influences the process of parameter estimation, control synthesis, as well as the stability of a closed system. The use of a regulator with the adaptation of parameters in a closed system from the very beginning of the control process, when the estimates of process parameters are not very accurate, usually does not allow for high-quality process control. In order to avoid undesirable values of input and output signals at this stage, it is advisable to use a signal of significant excitation to estimate the parameters and obtain the initial model in an open loop. After sufficient identification time, the model should be checked for proximity to the actual process. Such a preliminary stage should include the search for the structure of the model.

## II. FORMULATION OF THE PROBLEM

Consider a control object with input $u(t)$ and output $y(t)$, described by equations (3) - (6)

$$A(d)\ y(t) = B(d)\ u(t) + \xi(t), \tag{3}$$

where $A$ and $B$ – polynomials with the backward shift operator $d$:

$$(1 + a_1 d + \ldots + a_n d^m) y(t) = (b_1 d + \ldots + b_m d) u(t) + \xi(t), \tag{4}$$

$$y(t) = -a_1 y(t-1) - \ldots - a_n y(t-n) + b_1 u(t-1) + \ldots + b_m u(t-m) + \xi(t), \tag{5}$$

or

$$y(t) = \theta^T \varphi(t) + \xi(t), \tag{6}$$

where

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 6, Issue 3, March 2019

$$\theta = [a_1 \ ... \ a_n \vdots b_1 \ ... \ b_m]^T ,$$
$$\varphi(t) = [-y(t-1) \ ... \ -y(t-n) \vdots u(t-1) \ ... \ u(t-m)]^T .$$

It is assumed that stationary white noise $\xi(t)$ has zero expectation and variance $\sigma_\xi^2$. The combination of the parameter estimation algorithm and the control algorithm, for example, in the form of a controller with a minimum variance, is the adaptive or second level of process control.

Using the minimization criterion [2,17]

$$V_t(\theta) = \sum_{k=1}^{t} \beta(t, k) \left| y(k) - \theta^T \varphi(k) \right|^2$$

with

$$\beta(t,k) = \prod_{j=k+1}^{t} \lambda(j)$$

leads to the well-known recurrent least squares algorithm:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + P(t)\varphi(t)\varepsilon(t) ,$$
$$P(t) = \frac{1}{\lambda(t)} \left[ P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{\lambda(t) + \varphi^T(t)P(t-1)\varphi(t)} \right],$$
$$\varepsilon(t) = y(t) - \varphi^T(t)\hat{\theta}(t-1) ,$$

where $\lambda(t)$ - the forgetting coefficient.

An identifiable time-discrete system with varying parameters can be represented as the following model in the state space:

$$\left. \begin{array}{l} \theta(t-1) = \theta(t) + w(t) \\ y(t) = \varphi^T(t)\hat{\theta}(t) + \xi(t) \end{array} \right\} , \qquad (7)$$

where $\theta(t)$ is a $n$-dimensional vector containing the true system parameters at time $t$, $\varphi(t)$ - a vector containing old values of input and output signals, and $\xi(t)$ and $w(t)$ - perturbations, and $w(t)$ models the process of changing system parameters.

It is assumed that noise $\xi(t)$ is Gaussian with zero expectation and variance $R_2$. If disturbance $w(t)$ is Gaussian with a covariance matrix $R_1$, then the best estimate of the vector parameter $\theta$ is provided by a Kalman filter [1,2].

## III. SOLUTION OF THE TASK

One of the possibilities of modeling the process of changing parameters is associated with the use of a Gaussian distribution with a changing covariance matrix. If this change is known, then $R_1$ is replaced by the time-varying covariance matrix $R_1(t)$, and the Kalman filter, which determines the estimate $\hat{\theta}(t)$ of the parameter vector $\theta(t)$, is described by the equations:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1)) ,$$
$$K(t) = \frac{P(t-1)\varphi(t)}{R_2(t) + \varphi^T(t)P(t-1)\varphi(t)} ,$$
$$P(t) = P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{R_2(t) + \varphi^T(t)P(t-1)\varphi(t)} + R_1(t) .$$

Using classical identities [2], one can get

$$\left(\hat{\theta}(t) - \theta\right)^T P(t)^{-1} \left(\hat{\theta}(t) - \theta\right) + \sum_{n=0}^{t} \frac{\varepsilon(t)^2}{\varphi(t)P(t-1)\varphi(t) + 1} = \left(\hat{\theta}(0) - \theta\right)^T P(0)^{-1} \left(\hat{\theta}(0) - \theta\right) \le B_0^2 . \qquad (8)$$

Thus $\left\| \hat{\theta}(t) - \theta \right\|_{P(t)}^2 \le B_0^2$, $P(t)$ and $\theta$ will be limited and $P_1 : \hat{\theta}(t)$ limited to any $t$.

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 6, Issue 3, March 2019

From (8) it is possible to write down $\lim_{k\to\infty}\dfrac{\varepsilon_{(t)}^2}{\varphi^T(t)P(t-1)\varphi(t)+1}=0$

and thus

$$P_2: \left|y(t)-\varphi(t)\widehat{\theta}(t-1)\right| < \beta(t)\|\varphi(t)\|+\alpha(t)$$

at $\lim_{t\to\infty}\alpha(t)=\lim_{t\to\infty}\beta(t)=0$.

It can be shown that

$$\widehat{\theta}(t)=\theta+P(t)P(0)^{-1}(\widehat{\theta}(0)-\theta).$$

Then $\widehat{\theta}(\infty)$ exists and

$$P: \lim_{t\to\infty}\left\|\widehat{\theta}(t)-\widehat{\theta}(t-1)\right\|=0.$$

$\{P_i\}=\{P_1, P_2, P_3\}$ – is a classic set of properties used in many proofs of the global sustainability of adaptive control systems.

For the parameters that are constant most of the time, you can choose in the form:

$$w(t)=\begin{cases} v(t) & at \quad q \\ 0 & at \quad 1-q, \end{cases} \tag{9}$$

where $v(t)$ is Gaussian with zero expectation and covariance matrix $R_1$. Thus,

$$R_1(t)=\begin{cases} R_1 & at \quad q, \\ 0 & at \quad 1-q. \end{cases}$$

Since $w(t)$ is not Gaussian, the Kalman filter does not provide an optimal estimate. Problem (7) and (9) is the problem of nonlinear filtering. To solve it, we use an approach based on the use of an approximation in the form of a finite sum of Gaussian distributions.

A posteriori density $\theta(t)$ can be written in the form:

$$p\left[\theta(t)\,|\,y^{t-1}\right]=\sum_{i=1}^{M}\alpha_i(t)G_n(\theta(t),\overline{\theta}_i(t),P_i(t)), \tag{10}$$

where $\sum_{i=1}^{m}\alpha_i(t)=1$, and $\overline{\theta}_i(t)$ and $P_i(t)$ are expectation vectors and covariance matrices of various Gaussian distributions at time point $t$.

Following [2,18], it can be shown that in this case

$$p(\theta(t+1)\,|\,y^t)=\int_{-\infty}^{\infty}p(w(t))p(\theta(t+1)-w(t)\,|\,y^t)dv(t)=$$
$$=\sum_{i=1}^{M}\alpha_i'(t)\left\{(1-q)G_n\left(\theta(t+1),\overline{\theta}_i'(t),P_i'(t)\right)+qG_n\left(\theta(t+1),\overline{\theta}_i'(t),\left[P_i'(t)+R_1\right]\right)\right\}. \tag{11}$$

For the posterior distribution $p(\theta(t)\,|\,y^{t-1})$, defined by the expression (10), $p(\theta(t+1)\,|\,y^t)$ is determined by the expression (11). It follows that each Gaussian distribution splits into two. As a result, we obtain a rapidly increasing number of Gaussian components in the posterior density. To avoid this, it is advisable to use approximations consisting of cutting off $M$ branches. As a result, the most plausible component with the largest value of $\alpha_i'$ is retained, and the component with the smallest value of $\alpha_i'$ is cut off.

As a result, the algorithm is represented as follows:

$$P_i(t)=P_i(t-1)-\frac{P_i(t-1)\varphi(t)\varphi^T(t)P_i(t-1)}{R_2+\varphi^T(t)P_i(t-1)\varphi(t)},\ i=1,2,\ldots,M,$$

$$\varepsilon_i(t)=y(t)-\varphi^T(t)\overline{\theta}_i(t-1),$$

$$\overline{\theta}_i(t)=\overline{\theta}_i(t-1)+\frac{1}{R_2}P_i(t)\varphi(t)\varepsilon_i(t),$$

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 6, Issue 3, March 2019

$$\overline{\alpha}_i(t) = \frac{\alpha_i(t)}{\sqrt{(R_2 + \varphi^T(t)P_i(t-1)\varphi(t))}} \exp\left(-\frac{1}{2}\frac{\varepsilon_i^2(t)}{R_2 + \varphi^T(t)P_i(t-1)\varphi(t)}\right),$$

$$i_{\min} = \arg\min_i \overline{\alpha}_i(t),\ i_{\max} = \arg\max_i \overline{\alpha}_i(t),\ P_{i_{\min}}(t) = R_1 + P_{i_{\min}}(t),$$

$$\overline{\theta}_{i_{\min}}(t) = \overline{\theta}_{i_{\max}}(t),\ \ \overline{\alpha}_{i_{\min}}(t) = q,\ \ \alpha_i(t) = \frac{1}{\sum_{k=1}^{M}\overline{\alpha}_k(t)}\overline{\alpha}_i(t)\cdot$$

Score $\widehat{\theta}(t)$, the vector of parameters $\theta(t)$ is determined by the ratio of

$$\widehat{\theta}(t) = \sum_{i=1}^{M}\alpha_i(t)\overline{\theta}_i(t)\,.$$

## IV. CONCLUSION

The presented recurrent identification algorithms using multiple models and adapting their parameters based on the use of approximations in the form of a finite sum of Gaussian distributions result in consistent estimates and improve the quality of control processes in closed-loop control systems.

## REFERENCES


[1] Krasovsky A.A. 1987. The directory of the automatic control theory. Moscow: Science. – 712 p.
[2] Ljung L. Systems identification. The theory for the user: Translated from English. Moscow: Science. 1991.
[3] Emelyanov S.V., Korovin S.K., Rykov A.S. and others. Methods for identifying industrial objects in control systems. Kemerovo: Kuzbassvuzizdat, 2007. – 307 p.
[4] Antonov V., Terekhov V., Tyukin I. Adaptive control in technical systems. Tutorial. Publishing house: Publishing house of the St.-Petersburg university, 2001. - 244 p.
[5] Tsykunov A.M. Adaptive and robust control of dynamic objects at the exit. Publishing house: Fizmatlit, 2009. – 268 p.
[6] Kogan M.M., Neymark Yu.I. Adaptive management. Tutorial. -Gorky .: Publishing House of the State University, 1987. - 194 p.
[7] Pelzwerger S.B. Algorithmic support of assessment processes in dynamic systems in conditions of uncertainty. Moscow: Science, 2004. -116 p.
[8] Afanasyev V.N. Dynamic control systems with incomplete information: Algorithmic design. Publishing house: ComBook, 2007.
[9] Dorff R., Bishop R. Modern control systems. Moscow: Unimediistayl. 2002. - 822 p.
[10] Igamberdiev H.Z., Sevinov J.U., Zaripov O.O. Regulyarniy metodi i algoritmi sinteza adaptivnih sistem upravleniya s nastraivaemimi modelyami. - T.: TashGTU, 2014. - 160 p.
[11] Rajbman N.S., Chadeev V.M., On the concept of adaptive control systems wit h an identifier // Automation and Remote Control, 1982, 43:3, -pp.310–315.
[12] Bunich A.L. Control systems with identifier // Part I, Management problems, 2005, №5. –pp.83–91.
[13] Bunich A.L. Control systems with identifier // Part II, Management problems, 2006, №2. –pp.63–70.
[14] Korikov A.M., Sergeev V.L., Sevostyanov D.V., Sergeev P.V., Anikanov A.S. Adaptive dynamic identification and control systems in conditions of uncertainty // Reports of TUSUR, №2 (22), part II, 2010. –pp.230-233.
[15] Korikov A.M., Sergeev V.L., Sevostyanov D.V., Sergeev P.V. Adaptive integrated identification and management systems. Issues of design and development // Electronic tools and control systems: report. international scientific-practical conf. - Tomsk: Publishing House of IAO SB RAS, 2005. - Part II. - P. 58–61.
[16] Sergeev V.L. Integrated identification systems: studies. allowance. - Tomsk: Publishing house NTL, 2004. - 238 p.
[17] Izerman R. Digital control systems: Trans. from Englis. Moscow: Mir, 1984. – 541 p.
[18] Derevitskiy D.P., Fradkov A.A. 1981. Applied the theory of discrete adaptive control systems. Moscow: Science. – 216 p.