Optimal algorithm for parameter identification of nonlinear systems

Mykola Gumen, Tamara Gumen

Abstract - **An optimal algorithm for parametric identification of nonlinear systems based on procedures for smoothing the experimental data and evaluation of vector parameters of the object. Parametric identification is determined by the precision of experimental data and performance evaluation procedure.**

Keywords - **parameter identification, smoothing the experimental data.**

Parameter identification algorithm based on minimizing the error between the measurement output of the object and with a mathematical model for the requirements for entrance to the facility as well as model or white noise, or harmonic signals of different frequencies.

Identification problem is to construct an optimal model of the object after the observation of its input and output variables.

The process of identification of research involves solving a number of tasks: determining the object class; choice for this class of model parameters which can change depending on the accuracy of the measurements and conditions, selection criteria as identification, the formulation of the identification algorithm that uses to monitor the value of input and output variables.

The research subject of the dynamic nature described in this equation:

$$y_n = \sum_{j=1}^{m} C_j y_{n-j} + \sum_{j=1}^{k} C_{m-j} x_{n-j+1}, \qquad (1)$$

where x_n, y_n - discrete values of input and output values in the n clock cycle (in n moment time); $n = 1,2,...,N$ - the number of discrete time C_j - the unknown parameters of object; m, k - coefficients, that characterize the dimension of the object.

The optimal solution of (1) is a value C^* that satisfies the optimality conditions:

$$\nabla J(C) = M\{\nabla_C F[\varepsilon(z(n), C)]\} = 0, \qquad (2)$$

where $\nabla J(C)$ - average gradient of loss, $\nabla_C F[\varepsilon(z(n), C)]$ - gradient of loss function $F[\varepsilon(z(n), C)]$.

Vector equation (2) an equivalent system of nonlinear equations of relative C vector components. In general, when the vector C is nonlinear in (2), an explicit analytical expression for the optimal vector C^* found impossible even with full a priori information. Therefore have satisfied the various approximate $C(n)$ methods solving equation (2).

Most of them are related to the method of successive approximations. The essence of these methods is to replace the statistical equation (2) difference equation whose solution $C(n)$ with the increase $n \to \infty$ heading to the optimal vector C^*. This difference equation determines an algorithm of identification. In order to estimate $C(n)$ generated by the algorithm, went to the optimal solution C^* to $n \to \infty$ must be satisfied certain conditions of convergence.

The recurrent algorithms for determining parameters of the model C^* can not directly be used to determine the optimal solution C^*, if the average gradient of losses $\nabla J(C)$ not fully defined. So widespread were algorithms that do not require knowledge of the gradient of secondary losses $\nabla J(C)$, using the current information contained in the observations.

Algorithms solution equation (2) can be presented difference equation

$$C(n) = C(n-1) - A(n)\nabla_C F[\varepsilon(z(n), C(n-1))] \qquad (3)$$

dimension N_C, where amplifier diagonal matrix

$$A(n) = \begin{vmatrix} \gamma_1(n) & 0 & ... & 0 \\ 0 & \gamma_2(n) & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & 0 & \gamma_{N_C}(n) \end{vmatrix}. \qquad (4)$$

Scalar coefficients $\gamma_\nu(n),\ \nu = 1,..,N_C$ must satisfy the conditions

$$\text{а) } \gamma_\nu(n) > 0; \quad \text{б) } \sum_{n=1}^{\infty} \gamma_\nu(n) = \infty; \quad \text{в) } \sum_{n=1}^{\infty} \gamma_\nu^2(n) < \infty \qquad (5)$$

to ensure convergence of solution equation (4) (convergence in probability meaning they generate estimates $C(n)$ for the optimal solution C^*) for a wide class of loss functions $F[\cdot]$.

Conditions (5) have clear physical meaning. They provide a change of assessment $C(n)$ generated by recurrent algorithm, the average side antygradienta (condition *a*); reduction step of the algorithm is not so quick to estimate $C(n)$ longer change when you reach some arbitrary point (condition *b*), and not so slow that $C(n)$ rating, reaching an optimal point C^*, could not stop it (condition *c*).

Mykola Gumen – Kyiv National Aviation University, Levanevcky Str., 8/7, Kyiv, 03058, Ukraine, E-mail: fitgm@nau.edu.ua. Tamara Gumen – National Technical University of Ukraine “KPI”, Levanevcky Str., 8/7, Kyiv, 03058, Ukraine, E-mail: Bela_09@ukr.net