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Research of an Algorithm for Smoothing of Digital Measurement Information in Systems of Dynamic Change.

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Abstract. This article discusses the construction of a smoothing algorithm for digital measurement information in dynamic change systems using the Kalman filter. Elimination of errors and errors in the sensors is carried out by a smoothing algorithm which is the most optimal method in this case. Adaptive anti-aliasing filters are used as an adaptive device.

Key words: treatment, signals, algorithm, smoothing, Kalman filter, adaptive filters

Introduction. Digital signal processing (DSP) has long ceased to be only a section of radio engineering and communication theory. Digital signal processing methods are used in various fields: from medical diagnostics (computed tomography) to space monitoring (processing of Earth remote sensing data), from photography and video recording (image processing) to information and physical security. In order to competently use digital signal processing methods in these areas and correctly interpret their results, a specialist must imagine "what's inside?". And for this, first of all, you need to master the "alphabet" of this subject area, which includes models of digital signals, analysis apparatus and basic algorithms [1].
Many devices and sensors used in modern electronics, as well as in automation, have significant defects associated with low measurement accuracy and a high level of internal noise. Instrument errors can be divided into: systematic and random [2]. Systematic errors are usually estimated by calibration and compensated for over the course of the system.
A time series is a sequence of values that change over time. I will try to talk about some simple but effective approaches to working with such sequences in this article. There are a lot of examples of such data - currency quotes, sales volumes, customer requests, data in various applied sciences (sociology, meteorology, geology, observations in physics) and much more.
Series are a common and important form of data description, as they allow us to observe the entire history of the value we are interested in. This gives us the opportunity to judge the "typical" behavior of the quantity and the deviations from such behavior.

Materials and methods. When studying real processes, as a rule, instead of a true physical quantity, a random value $x(j)$ is recorded, which is an additive mixture of quantity $v(j)$ itself and interference $k(j)$, that is, $x(j) = v(j) + k(j)$. Interference $k(j)$ can be generated directly in the object under study, fall into it from the outside, or be an accidental chains of measurement and registration.
The presence of interference in sequence $x(j)$ makes it difficult to obtain reliable information about the process under study. Therefore, the sequence $x(j)$ is subjected to primary processing, the purpose of which is smoothing, that is, the complete or partial elimination of interference $k(j)$. The smoothing of the discrete sequence $x(j)$ is carried out using special algorithms. The aim of the work is to study algorithms for smoothing experimental data presented as finite discrete sequences.
Each measurement is the sum of a useful signal and interference of various types: noise, impulse noise, interference. Errors - noise occurs in the controlled object due to the imperfection of existing measuring transducers, the random nature of the processes occurring in them, and in the sensors themselves, in the

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electronic channels of the devices. Pickups include external radio interference, changes in environmental conditions, etc. [3]. Impulse interference is aperiodic bursts of short duration, the moments of occurrence of which, their polarity and amplitude are random. A large number of interference sources allows in many cases to assume that they are normally distributed. The main task in digital signal processing is to obtain, based on an array of digital data, the most accurate estimate of the original useful analog signal that generated this data [4, 6]. Intelligent control algorithms are even more sensitive to solving this problem. Therefore, the developed advising control system for a rotary cement kiln [5, 10] needs to be supplemented with a subsystem for processing input signals, the basis of which will be the smoothing algorithm developed in this work.
When eliminating random errors in sensors, it is necessary to apply smoothing algorithms based on the Kalman filter: Models of the instrument state and observations can be written in the following form:

$$x(j+1) = F(j+1, j)x(j) + G(j)w(j). \quad (1)$$

$$z(j) = H(j)x(j) + v(j). \quad (2)$$

We take the a priori data as:

$$E\{w(j)\} = 0, E\{v(j)\} = 0, E\{x(0)\} = \mu(0),$$

$$\text{cov}\{w(j), w(k)\} = V_w(j)\delta_K(j-K),$$

$$\text{cov}\{v(j), v(k)\} = V_v(j)\delta_K(j-K),$$

$$\text{cov}\{w(j), v(k)\} = \text{cov}\{x(0), w(k)\} = \text{cov}\{x(0), v(k)\} = 0,$$

$$\text{var}\{x(0)\} = V_{\tilde{x}}(0).$$

So, smoothing algorithms based on the Kalman filter can be written as:

$$\hat{x}(j) = F(j, j-1)\hat{x}(j-1) + K(j)[z(j) - H(j)F(j, j-1)\hat{x}(j-1)]. \quad (3)$$

$$K(j) = V_{\tilde{x}}(j/j-1)H^T(j)[H(j)V_{\tilde{x}}(j/j-1)H^T(j) + V_v(j)]^{-1} = \\ = V_{\hat{x}}(j)H^T(j)V_v^{-1}(j). \quad (4)$$

$$V_{\tilde{x}}(k/N) = V_{\tilde{x}}(k) + A(k)[V_{\tilde{x}}(k+1/N) - V_{\tilde{x}}(k+1/k)]A^T(k). \quad (5)$$

$$\hat{x}(N/N) = \hat{x}(N); V_{\hat{x}}(N/N) = V_{\hat{x}}.(N)$$

Discussion. The classical Kalman filter makes it possible to obtain optimal estimates of a random process under the condition of stationary of the measuring noises or the availability of a priori information about the change in their intensity. It is rather difficult to obtain and use accurate information about the change in the intensity of the noise of the sensors, since it depends on the random conditions of the functioning of the sensor and on the instability of the noise characteristics of various sensors [7, 8].
These errors can be compensated by using smoothing filters; they are adaptive to changes in the measurement noise intensity. A similar approach to the construction of adaptive algorithms based on the Kalman filter is to expand the state vector by including an a priori unknown measurement noise intensity. With this approach, the equations for the covariance matrices of estimation errors (the Riccati equations) become dependent on the measurement results and must be integrated together with the equations for the state vector estimates. This leads to an increase in computational costs when implementing the filter. In order to reduce the computational cost of adaptation, a smoothing algorithm is proposed that has the Kalman filter structure and is distinguished by preliminary statistical processing of measurement residuals [9, 11].
You can automatically select the optimal parameter values using a systematic search in the parameter value space and minimizing the sum of squared deviations of the smoothed series from the original.
The methods described are quite simple, easy to apply, and a good starting point for structure analysis and time series forecasting.
First-order adaptive smoothing filters are designed to process scalar signals of information sensors using an a priori signal model in the form of a first-order stochastic differential (difference) equation.
Let a discrete process *x(k)* enter the sensor input, the a priori model of which is described by the equation:

$$x(k+1) = \alpha x(k) + \xi(k+1), \quad (6)$$

- grade update step; T_x - time constant of the forming filter of the process $x(k); \xi(k+1)$ - discrete centered random process, the values of which are not correlated at neighboring counting steps $M[\xi(k+1)\xi(k)] = 0$.

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The sensor measures x(k) values with a random error $x^*(k)$:

$$x^*(k) = x(k) + \eta(k).\ (7)$$

It is assumed that the systematic component of the error $\Delta x(k)$ is absent (or is compensated at the output of the sensor). Random component $\eta(k)$ is a discrete non-stationary centered random process, the values of which at neighboring counting steps are not correlated with each other $(M[\eta(k+1)\eta(k)] = 0)$.

For a discrete process (6), taking into account relation (7), it is required to obtain a filtering algorithm of the Kalman structure, in which the transformation coefficient $k_\Phi(k)$ adapts to a change in the intensity of the process $\eta(k)$ [11, 2]

For equation (6), a quasi-optimal estimate of process $\hat{x}(k)$ can be obtained based on the recursive relation:

$$\hat{x}(k+1) = \alpha\hat{x}(k) + k_\Phi[x^*(k+1) - \alpha\hat{x}(k)]\ (8)$$

where $k_\Phi(k)$ is the filter conversion factor; $x^*(k+1)$ - measured value of the sensor signal at step *(k + 1)*.

To determine the conversion coefficient of a filter $k_\Phi(k)$, you must calculate estimates at each step of the account $\hat{M}[v(k+1)v(k)]$ and $\hat{M}[v^2(k+1)]$, where $v(k+1) = x^*(k+1) - \alpha\hat{x}(k)$ the measurement is not at the point $v(k+1) = x^*(k+1) - \alpha\hat{x}(k)$ in time t_{k+1}. Estimates of values $\hat{M}[v(k+1)v(k)]$ and $\hat{M}[v^2(k+1)]$, are located by averaging the corresponding works on the sliding interval T_0, which contains *N* cycles of calculating the value of the measurement $x(k): T_0 = N\Delta t$. At the same time for satisfactory operation of the algorithm it is enough to accept *N = 50 ÷ 100*.

Calculation of the coefficient is made by the following algorithm:

1. At each step of the reference K the *N*-dimensional vector *Q* is formed, the elements of which are the residuals of the measurements calculated on the previous *N-1* steps of the evaluation update and in this step:

$$Q^T = \{q_1, q_2, ...q_n\} = \{v(k), v(k-1), ..., v(k-N+1)\}.$$

2. In addition, at each step of the account is memorized vector r. Formed in the previous step:

$$P^T = \{p_1, p_2, ...p_n\} = \{v(k-1), v(k-2), ..., v(k-N)\}.$$

3. Scalar works are calculated:

$$S_1 = Q^T Q; S_2 = Q^T P.$$

4. As estimations of mathematical expectations of covariance of residuals are accepted

$$\hat{M}[v^2(k+1)] \approx \frac{S_1}{N};\ \hat{M}[v(k+1)v(k)] \approx \frac{S_2}{N}$$

The filter $k_\Phi(k)$ conversion factor is calculated by the formula:

$$k_\Phi = \frac{\left|\hat{M}[v(k+1)v(k)]\right|}{\hat{M}[v^2(k+1)]} = \frac{S_2}{S_1}\ (9)$$

The given algorithms allow to receive and use the reliable priori information on change of intensity of noises, and to exclude influence of instability of noise characteristics of various sensors.

Conclusion. The proposed algorithm is based on the results of work [2], which shows that the Kalman filter coefficients matrix can be obtained on the basis of the information contained in the covariance matrices of the updating sequence of measurements. Algorithms of calculation of coefficients of the filter, received in work [3], are improved that preliminary statistical processing of residuals of measurements is carried out on a sliding interval of time. This ensures a higher accuracy of the filter coefficient determination.

Reference

1. Коберниченко В. Г. Основы цифровой обработки сигналов//Учебное пособие, Екатеринбург Издательство Уральского университета, 2018. — 150 с. ISBN 978-5-7996-2464-4
2. Малкин В.А. «Адаптивные фильтры сглаживания сигналов датчиков в системах микроавионики», Военная академия Республики Беларусь, г. Минск, Республика Беларусь 2017

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Date of Publication:24-01-2023

3. Коротаев В.В. Точность измерительных оптико-электронных приборов и систем: учеб. пособие. СПб.: НИУ ИТМО, 2011. 41 с.
4. Халимон В.И., Комаров П.И., Жуковец Ю.Э. Автоматизированный выбор программного фильтра: методические указания к лабораторной работе. СПб.: СПбГТИ(ТУ). Каф. систем автоматизированного проектирования и управления, 1999. 35 с.
5. Каламбет Ю.А., Мальцев С.А., Козьмин Ю.П. Фильтрация шумов: окончательное решение проблемы // Аналитика. 2011. №1. С. 50-56.
6. Магергут В.З. Копылов А.С. Степовой А.А. Нейро - нечеткое управление вращающейся печью для обжига цементного клинкера // Приборы и системы. Управление, контроль, диагностика. №11. 2014 г. С. 8-13
7. Atajonov M.O, Nimatov S.J, Rakhmatullaev A.I, Sadullaev A.B. Formalization of the dynamics of the functioning of petrochemical complexes based on the theory of fuzzy sets and fuzzy logic// AIP Conference Proceedings 2552, 050014 (2023);. -Published Online: 05 January 2023, https://doi.org/10.1063/5.0112403
8. Atajonova S. B. Control of multidimensional discrete objects by a terminal management/https:// Journal of Academic Research and Trends in Educational Sciences 2 (1), 56-61
9. Atajonov M.O Methods and models for diagnosing technological objects// Scientific and technical journal machine building. Issue 5, Vol. I, 2022
10. Sidikov I.H, Atajonov M.O, Atajonova S.B., Fuzzy-Situational Diagnostics of Technological Safety of Petrochemical Plants// J. EAST, 2019 № 4 pp 182-186
11. Sidikov I.H, Atajonova S.B., Imitation model of the chemical reactor control system// Chemical Technology, Control and Management 2018 (1), 108-112