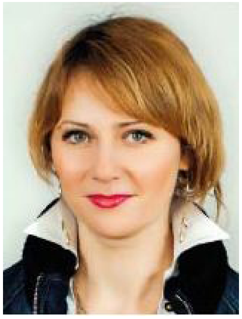
Identification of spatial and temporal model of concentrating production processes on the basis of the Volterra kernel conversion



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Abstract
An approach to the identification of a spatial and temporal model of iron ore raw material processing on mining and treating enterprises using Volterra kernels is proposed
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In general, linear distributed parameter systems (DPS) can be represented by the impulse response function: Green's functions and a kernel [1, 2]. In order to obtain a model of unknown nonlinear system with a distributed parameters, based on the idea of spatial and temporal separation the Green's function must be expanded in a series of Volterra. Spatial and temporal Volterra model can be built by the addition of spatial variables in the traditional model of Volterra.

Linear continuous DPS can be represented as a linear mapping of input $u(x,t)$ on the output $y(x,y)$, where $x \in \Omega$ – is a spatial variable. This mapping can be expressed by a Fredholm integral equation of the first kind, containing the integrable Green's kernel - function) [1-3].

$$y(x,t) = \int_{\Omega}\int_{0}^{t} \gamma(x,\zeta,t,\tau) u(\zeta,\tau) d\tau\, d\zeta \qquad (1)$$

At the same time, a system with concentrated parameters, which generally is described by

$$y(t) = N(\{u(\tau)\}) + d(t) \qquad (2)$$

where $\{u(\tau)\} = \{u(\tau) \mid \tau = 1,\dots,t\}$ – is the input signal; t – is the discrete time; y – is the output; d – are the stochastic perturbations, N - is the fading memory feature operator, can be approximated by a discrete Volterra model [1, 4]

$$y(t)=\sum_{r=1}^{\infty}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_\gamma=0}^{t}\gamma_r(t,\tau_1,\ldots,\tau_r)\prod_{v=1}^{r}(\tau_v) \quad (3)$$

Conversion (1) and (3), for system with a distributed parameters allows to obtain

$$y(x,t)=N(\{u(\zeta,\tau)\})+d(x,t) \quad (4)$$

where $\{u(\zeta,t)\}=\{u(\zeta,t)\,|\,\zeta\in\Omega,\tau=1,\ldots,t\}$ is the input, spatiotemporal Volterra model is constructed by adding the space of variables to the traditional Volterra model

where γ_r –is the function r-th order of spatial and temporal Volterra kernel, which indicates change in the input in the space of $\zeta_1,\ldots,\zeta_r$ and time $\tau_1,\ldots\tau_r$. As in (1), the spatiotemporal variables in (5) are symmetrical. The Green's function of the first kind of spatiotemporal Volterra model, and kernel of the spatiotemporal Volterra model can be considered as multi-dimensional generalization of the Green's function [1,2].

Model (5) can operate both for time-varying and fixed systems. For currently invariant time system, the kernel will be invariant and can be represented as follows [1]

$$y(x,t)=\sum_{r=1}^{\infty}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_\gamma=0}^{t}\gamma_r(x,\zeta_1,\ldots,\zeta_r,t,\tau_1,\ldots,\tau_r)\prod_{v=1}^{r}u(\zeta_v,\tau_v)d\zeta_v \quad (5)$$

$$\gamma_r(x,\zeta_1,\ldots,\zeta_r,t,\tau_1,\ldots,\tau_r)=\gamma_r(x,\zeta_1,\ldots,\zeta_r,t-\tau_1,\ldots,t-\tau_r) \quad (6)$$

Similarly, the model (5) can also operate in a space of changing or space-invariant system.

When the model is uniform in the spatial domain, there

$$\gamma_r(x,\zeta_1,\ldots,\zeta_r,t,\tau_1,\ldots,\tau_r)=\gamma_r(x-\zeta_1,\ldots,x-\zeta_r,t,\tau_1,\ldots,\tau_r) \quad (7)$$

By substituting (6) in (5) we can obtain the following expressions

$$y(x,t)=\sum_{r=1}^{\infty}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_\gamma=0}^{t}\gamma_r(x,\zeta_1,\ldots,\zeta_r,t,\tau_1,\ldots,\tau_r)\prod_{v=1}^{r}u(\zeta_v,t-\tau_v)d\zeta_v \quad (8)$$

Model (8) is not applicable because of its infinite order. In practice, [1, 4], the higher-order terms can be neglected and consider only the first R kernels

$$y(x,t)=\sum_{r=1}^{R}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_\gamma=0}^{t}\gamma_r(x,\zeta_1,\ldots,\zeta_r,t,\tau_1,\ldots,\tau_r)\prod_{v=1}^{r}u(\zeta_v,t-\tau_v)d\zeta_v+\upsilon(x,t) \quad (9)$$

where the last term $\upsilon(x,t)$ includes the nonmodelable dynamics and external noise. Modeling accuracy and complexity of the model can be controlled by the R order. Assuming that the kernels in (9) are absolutely integrable on the time domain $[0,\infty)$ at any point of space of x and ζ, this means that the corresponding spatial and temporal Volterra model is stable, i.e. it can be represented by a orthonormal temporary basis functions. The kernels should be expanded on the basis of input of $\{\psi_i(x)\}_{i=1}^{m}$, output of $\{\varphi_i(x)\}_{i=1}^{n}$ and temporal base of $\{\varphi_i(t)\}_{i=1}^{q}$

$$y(x,t)=\int_{\Omega}\int_{0}^{t}\gamma(x,\zeta,t,\tau)u(\zeta,\tau)d\tau\,d\zeta \quad (10)$$

where $\theta^{(r)}_{j_1\ldots j_r k_1\ldots k_r}$ - is the corresponding constant coefficient.

The parameters n and q have to be infinite for DPS. In practice, for most parabolic systems, the finite n and q are sufficiently realistic assumption [1-5].

Obviously, it depends on the required accuracy of the simulation. On the other hand, n is also dependent on the speed mode and the type of spatial basis functions, whereas q is also associated with the system dynamics complexity.

After the kernels in (10) are reduced using spatiotemporal synthesis, from the estimated parameters (9) the spatial and temporal Volterra model can be obtained. A graphical representation of second and third order kernels, resulting from the control system identification of distributed process of an iron ore raw materials beneficiation is shown in Fig. 1.

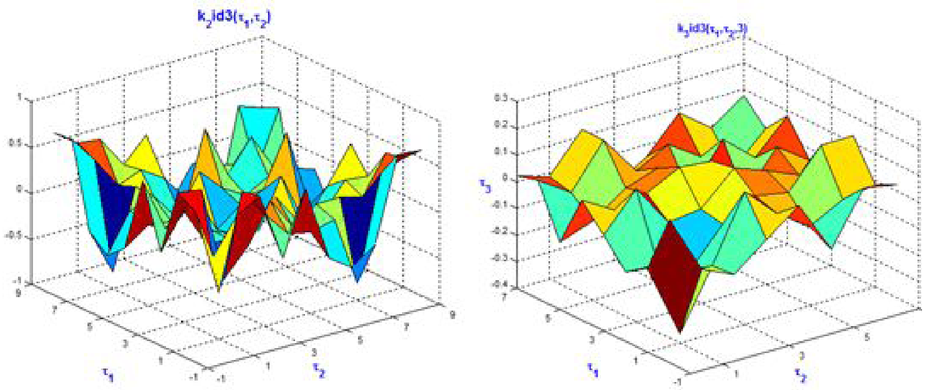
Identification results and experimental data are presented in Fig. 2.

The spatial and temporal Volterra model (9) can be converted into a state space form [1]. The transfer functions of the Laguerre network in implementing have the next form

$$\Xi_1(s)=\sqrt{2p}/(s+p), \Xi_2(s)=\ldots=\Xi_q(s)=(s-p)/(s+p) \quad (11)$$

and can be obtained from Laguerre functions, which is given by the i-th Laplace transform

$$\varphi_i(s)=\sqrt{2p}(s-p)^{i-1}/(s+p)^i, i=1\ldots\infty, p>0 \quad (12)$$



a) b)

Figure 1. The result of the Volterra kernels identification:
a) the second order; b) The third order core cross-section

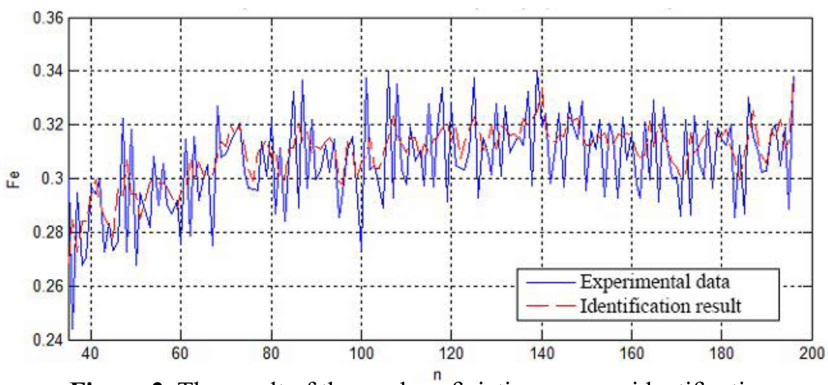


Figure 2. The result of the ore beneficiation process identification

Representation of the Laguerre network at realization of this procedure is shown in Figure 3.

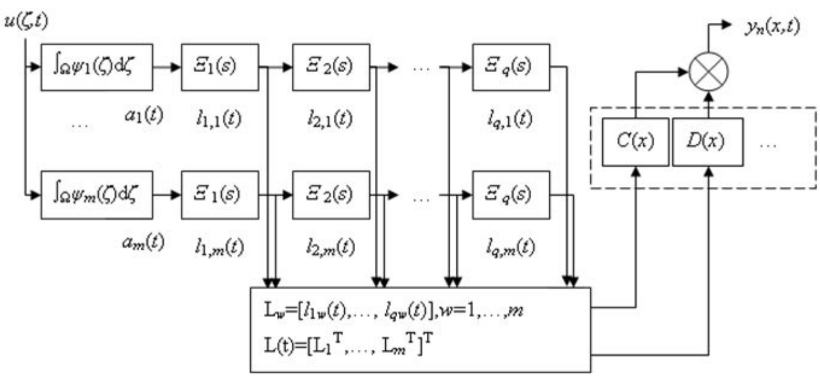


Figure 3. Volterra model implementation in the state space using the Laguerre network

A number of studies [5-11] notes that in the control process of iron ore raw material beneficiation should take into account the characteristics of some of its mineralogical and technological varieties, the change of which is significantly effect on quality of the concentrating production process models identification. Therefore, it is advisable in the future to explore the techniques of adaptive and robust control of distributed processes of iron ore raw material beneficiation varieties.

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