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METHOD OF OPTIMAL LINEAR EXTRAPOLATION OF VECTOR RANDOM SEQUENCES WITH FULL CONSIDERATION OF CORRELATION CONNECTIONS FOR EACH COMPONENT

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The work is devoted to solving important scientific and technical problems of formation of the optimal method of mean-square linear extrapolation implementations of vector random sequences of any number of known values used for the forecast. The resulting method, in contrast to existing solutions prediction problem, take full account of a priori information about the target sequence for each component. Forecast model is synthesized based on the linear vector of the canonical decomposition of the random sequences. The formula for determining the mean square error of extrapolation, which allows us to estimate the accuracy of solving the problem of the prediction by the proposed method for some fixed number of known values and components of the vector sequence. The paper also shows a block-diagram of an algorithm for determining the parameters of the proposed method.

Key words: vector random sequences, linear canonical decomposition algorithm extrapolation

The solution of many actual scientific and technical problems associated with the use of algorithms and extrapolating devices, which are known ie observable part of the process make it possible to estimate the unknown inaccessible part of it. In particular extrapolating algorithms used in automatic control systems and objects inertial systems with delay. Exceptionally widely spread algorithm linear prediction vocoders used in modern digital communication systems, in the compressed audio and video signal [1]. It is also widely used predictive algorithms based on neural networks, Kalman-Bucy filter, group method of data and some others [2-16]. However, despite this diversity, the need for high-speed, robust and highly accurate algorithms and devices of the forecast continues to be relevant in the present and in the future.

Assume that the random vector sequence $\{\overline{X}\}=\{X_1(i)...X_h(i)...X_H(i)\}$ in the study a number of points $t_i, i=\overline{1,I}$ given full matrix functions $M[X_h(i)]$, $h=\overline{1,H}$, $i=\overline{1,I}$; $M[X_\lambda(\nu)X_h(i)]$, $\nu,i=\overline{1,I}$, $\lambda,h=\overline{1,H}$. It is necessary to synthesize a method of predicting the future values of a random sequence $\{\overline{X}\}$ of known values $x_h(i),\ i=\overline{1,k},\ k<I,\ h=\overline{1,H}$, which are obtained by measuring the target sequence on the observation interval $[t_1...t_k]$.

Method, in contrast to existing solutions prediction problem, take full account of a priori information about the target sequence for each component.

The most universal method in terms of the restrictions that are imposed on the predicted sequences is the algorithm of extrapolation [17]:

$$m_h^{(r_1,...,r_k)}(i)=\begin{cases} M[X_h(i)],\ k=0,\ i=\overline{1,I}, \\ m_h^{(r_1,...,r_k-1)}(i)+\left[x_{r_k}(k)-m_{r_k}^{(r_1,...,r_k-1)}(\mu)\right]\times \\ \times\varphi_{hk}^{(r_k)}(i),\ h=\overline{1,H},\ i=\overline{k+1,I}. \end{cases} \quad (1)$$

In the expression (1) $r_\mu,\ \mu=\overline{1,k}$ - number of components in the section t_μ. The parameters of the algorithm (1) are elements of the canonical decomposition:

$$X_h(i)=M[X_h(i)]+\sum_{\lambda=1}^{h}\sum_{\nu=1}^{i}V_\nu^{(\lambda)}\varphi_{h\nu}^{(\lambda)}(i),\quad h=\overline{1,H}, i=\overline{1,I}. \quad (2)$$

Relations for their definitions are of the form:

$$\begin{gathered} V_1^{(1)}=X_1(1)-M[X_1(i)], \\ V_i^{(h)}=X_h(i)-M[X_h(i)]-\sum_{\lambda=1}^{h}\sum_{\nu=1}^{i-1}V_\nu^{(\lambda)}\varphi_{h\nu}^{(\lambda)}(i), \\ h=\overline{1,H}, i=\overline{1,I}; \end{gathered} \quad (3)$$

$$\begin{gathered} D_1^{(1)}=D_1(1), \\ D_i^{(h)}=D_h(i)-\sum_{\lambda=1}^{h}\sum_{\nu=1}^{i-1}D_\nu^{(\lambda)}\left[\varphi_{h\nu}^{(\lambda)}(i)\right]^2, \\ h=\overline{1,H}, i=\overline{1,I}; \end{gathered} \quad (4)$$

$$\varphi_{h\nu}^{(\lambda)}(i) = \frac{1}{D_\nu^{(\lambda)}} M\left[V_\nu^{(\lambda)}\left(X_h(i) - M\left[X_h(i)\right]\right)\right],$$
$$h = \overline{1,H},\ \lambda = \overline{1,h},\ \nu, i = \overline{1,I}. \quad (5)$$

Expression (1) in the framework described in the canonical decomposition (2) the probability linear relations of sequence $\{\overline{X}\}$ allows to get the best result in the mean-square values of extrapolation $x_h(i),\ i = \overline{k+1,I},\ h = \overline{1,H}.$ However, the full properties of the target sequence $\{\overline{X}\}$ in (2) takes into account only for component $\{X_H\}$(for $\{X_h\},\ h < H$ it is not used in the formula (2) of interrelation communication $\{X_h\}$ with $\{X_{h+j}\},\ j = \overline{1, H-h}$) and, thus, only this component results extrapolation algorithm (1) can be considered strictly optimal for the available capacity of a priori information about the investigated vector random sequence. For other component characteristics estimation accuracy (1) can be improved by increasing the amount of a priori information, which is used for the forecast.

In order to eliminate this disadvantage use to generate a extrapolation algorithm a canonical decomposition [18-20] sequences $\{\overline{X}\}$ with full consideration of interrelation connections for each component:

$$X_h(i) = M\left[X_h(i)\right] + \sum_{\nu=1}^{i-1}\sum_{\lambda=1}^{H} V_\nu^{(\lambda)}\varphi_{h\nu}^{(\lambda)}(i) +$$
$$+\sum_{\lambda=1}^{h} V_i^{(\lambda)}\varphi_{hi}^{(\lambda)}(i),\ i = \overline{1,I}. \quad (6)$$

Elements of the expansion (6) are given by:

$$V_\nu^{(\lambda)} = X_\lambda(\nu) - M\left[X_\lambda(\nu)\right] -$$
$$-\sum_{\mu=1}^{\nu-1}\sum_{j=1}^{H} V_\mu^{(j)}\varphi_{\lambda\mu}^{(j)}(\nu) - \sum_{j=1}^{\lambda-1} V_\nu^{(j)}\varphi_{\lambda\nu}^{(j)}(\nu), \nu = \overline{1,I}; \quad (7)$$

$$D_\lambda(\nu) = M\left[\left\{V_\nu^{(\lambda)}\right\}^2\right] = M\left[\left\{X_\lambda(\nu)\right\}^2\right] -$$
$$-M^2\left[X_\lambda(\nu)\right] - \sum_{\mu=1}^{\nu-1}\sum_{j=1}^{H} D_j(\mu)\left\{\varphi_{\lambda\mu}^{(j)}(\nu)\right\}^2 -$$
$$-\sum_{j=1}^{\lambda-1} D_j(\nu)\left\{\varphi_{\lambda\nu}^{(j)}(\nu)\right\}^2,\ \nu = \overline{1,I}; \quad (8)$$

$$\varphi_{h\nu}^{(\lambda)}(i) = \frac{M\left[V_\nu^{(\lambda)}\left(X_h(i) - M[X_h(i)]\right)\right]}{M\left[\left\{V_\nu^{(\lambda)}\right\}^2\right]} =$$
$$= \frac{1}{D_\lambda(\nu)}(M\left[X_\lambda(\nu)X_h(i)\right] - M\left[X_\lambda(\nu)\right]\times \quad (9)$$

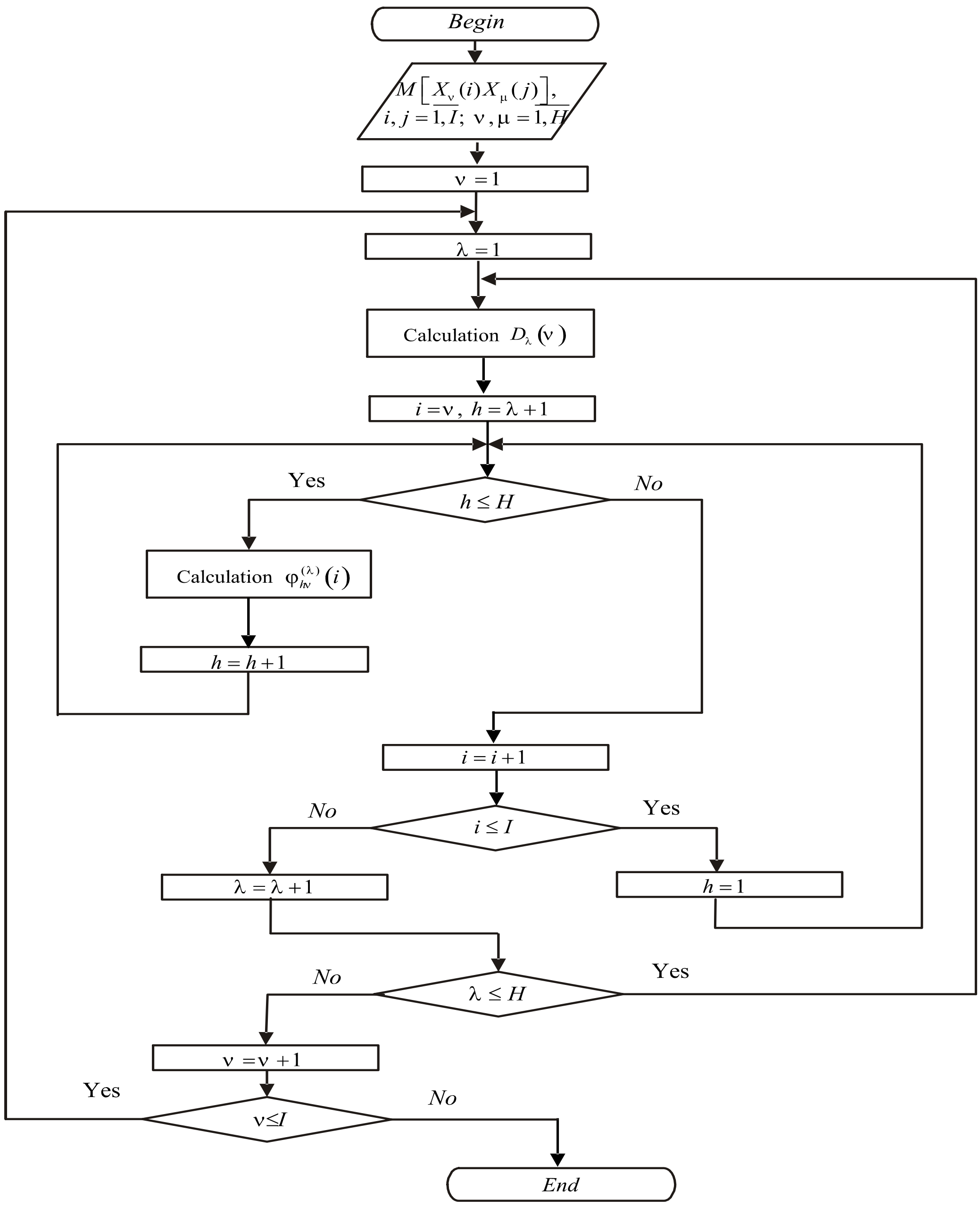
$$\times M\left[X_h\left(i\right)\right]-\sum_{\mu=1}^{\nu-1}\sum_{j=1}^{H}D_j\left(\mu\right)\varphi_{\lambda\mu}^{(j)}\left(\nu\right)\varphi_{h\mu}^{(j)}\left(i\right)-$$

$$-\sum_{j=1}^{\lambda-1}D_j\left(\nu\right)\varphi_{\lambda\nu}^{(j)}\left(\nu\right)\varphi_{h\nu}^{(j)}\left(i\right)),\ \lambda=\overline{1,h},\ \nu=\overline{1,i}.$$

The coordinate functions $\varphi_{h\nu}^{(\lambda)}\left(i\right),\ \ h,\lambda=\overline{1,H},\ \ \nu,i=\overline{1,I}$ are characterized by the following properties:

$$\varphi_{h\nu}^{(\lambda)}\left(i\right)=\begin{cases}1,\ h=\lambda\,\&\,\nu=i;\\0,\ i<\nu.\end{cases} \qquad (10)$$

Block diagram of the algorithm for calculating the parameters of the canonical decomposition (6) is shown in pic. 1.



Pic. 1. Block diagram of the algorithm for calculating the parameters of the canonical decomposition (6)

Suppose that at time $\mu = 1$ known value $X_1(1) = x_1(1)$ of the first component $\{X_1\}$ sequence $\{\overline{X}\}$ and thus knows the value of the random coefficient $V_1^{(1)} = v_1^{(1)}:\ v_1^{(1)} = x_1(1) - M[X_1(1)]$.

Substituting $v_1^{(1)}$ into (6) gives:

$$X_h^{(1,1)}(i) = M[X_h(i)] + \left(x_1(1) - M[X_1(1)]\right)\varphi_{h1}^{(1)}(i) +$$
$$+\sum_{\lambda=2}^{H} V_1^{(\lambda)}\varphi_{h1}^{(\lambda)}(i) +$$
$$\sum_{\nu=2}^{i-1}\sum_{\lambda=1}^{H} V_\nu^{(\lambda)}\varphi_{h\nu}^{(\lambda)}(i) + \sum_{\lambda=1}^{h} V_i^{(\lambda)}\varphi_{hi}^{(\lambda)}(i),\ i = \overline{1,I}. \tag{11}$$

$X_h^{(1,1)}(i) = X_h(i / x_1(1))$ - a posteriori random sequence in which the component $\{X_1\}$ passes through the coordinate $x_1(1)$ at time $\mu = 1$.

Application to the operation of the expectation (11) provides an estimate of the future value:

$$m_h^{(1,1)}(i) = M[X_h(i)] + \left(x_1(1) - M[X_1(1)]\right)\varphi_{h1}^{(1)}(i). \tag{12}$$

Let us consider the value $x_2(1)$ of the same implementation. For it is the expansion (11) that allows you to specify the value of the coefficient $V_2^{(1)} = v_2^{(1)}$. In view of (12) the expression for the coefficient $v_2^{(1)}$ can be written as:

$$v_2^{(1)} = x_2(1) - m_2^{(1,1)}(1). \tag{13}$$

that allows to record:

$$m_h^{(1,2)}(i) = m_h^{(1,1)}(i) + \left[x_2(1) - m_2^{(1,1)}(i)\right]\varphi_{h1}^{(2)}(i). \tag{14}$$

With a further increase in the a posteriori information is used to forecast the resulting pattern gives a generalization of extrapolation algorithm for an arbitrary number of measurement points

$$m_h^{(\mu,l)}(i) = \begin{cases} M[X_h(i)],\ \mu = 0; \\ m_h^{(\mu,l-1)}(i) + \left[x_l(\mu) - m_l^{(\mu,l-1)}(\mu)\right]\varphi_{h\mu}^{(l)}(i), \\ l \neq 1,\ \mu = \overline{1,k},\ i = \overline{k+1,I}; \\ m_h^{(\mu,H)}(i) + \left[x_1(\mu) - m_1^{(\mu-1,H)}(\mu)\right]\varphi_{h\mu}^{(1)}(i), \\ l = 1,\ \mu = \overline{1,k},\ i = \overline{k+1,I}. \end{cases} \tag{14}$$

$m_h^{(\mu,l)}(i) = M\left[X_h(i) / x_\lambda(\nu), \lambda = \overline{1,H}, \nu = \overline{1,\mu-1}; x_j(\mu), j = \overline{1,l}\right]$, $h = \overline{1,H},\ i = \overline{k,I}$ - optimal for the criterion of the minimum mean square error of the forecast estimates of future values of the target sequence, provided that the values of $x_{\lambda}(\nu),\ \lambda=\overline{1,H},\ \nu=\overline{1,\mu-1};\ x_j(\mu),\ j=\overline{1,l}$

The first expression of the algorithm (15) corresponds to the case where a posteriori information is not provided, in the second ratio consistently recurrently known value is accounted for vector random sequences for the fixed time, and the third expression moves to the next point in time for the further accumulation of information, which is used to forecast .

The mean square error of extrapolation algorithm (15) is given by

$$E_h^{(\mu,l)}(i)=D_{X_h}(i)-\sum_{\nu=1}^{\mu-1}\sum_{\lambda=1}^{H}V_{\nu}^{(\lambda)}\varphi_{h\nu}^{(\lambda)}(i)-\sum_{j=1}^{l}V_{\mu}^{(j)}\varphi_{h\mu}^{(j)}(i),\ i=\overline{k+1,I}.$$

In the paper is formed prediction algorithm vector random sequences. Method well as the canonical decomposition, put in its basis, fully take into account for each component of all known information about the target sequence. This ensures the absolute minimum mean square error linear prediction for an arbitrary component. It is also an expression for the mean square error of extrapolation, which allows to evaluate the quality of solving the problem of forecasting for any number of dimensions and the number of components of the study of vector random sequences.

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Способ оптимальной линейной экстраполяции векторных случайных последовательств с полным рассмотрением корреляционных соединений для каждого компонента. И. А. Атаманюк, Ю. П. Кондратенко

Работа посвящена решению важных научно-технических задач формирования оптимального метода среднеквадратичных линейных экстраполяционных реализаций векторных случайных последовательностей любого числа известных значений, используемых для прогноза. Полученный метод, в отличие от проблемы прогнозирования существующих решений, полностью учитывает априорную информацию о целевой последовательности для каждого компонента. Прогнозная модель синтезируется на основе линейного вектора канонического разложения случайных последовательностей. Формула для определения среднеквадратической ошибки экстраполяции, которая позволяет оценить точность решения задачи прогнозирования предложенным методом для некоторого фиксированного числа известных значений и компонент векторной последовательности. В работе также показана блок-схема алгоритма для определения параметров предложенного метода.

Спосіб оптимальної лінійної екстраполяції векторних випадкових послідовностей з повним розглядом кореляційних з'єднань для кожного компонента. І. А. Атаманюк, Ю. П. Кондратенко

Робота присвячена вирішенню важливих науково-технічних завдань формування оптимального методу середньоквадратичних лінійних екстраполяціонних реалізацій векторних випадкових послідовностей будь-якого числа відомих значень, використовуваних для прогнозу. Отриманий метод, на відміну від проблеми прогнозування існуючих рішень, повністю враховує апріорну інформацію про цільову послідовності для кожного компонента. Прогнозна модель синтезується на основі лінійного вектора канонічного розкладання випадкових послідовностей. Формула для визначення середньоквадратичної помилки екстраполяції, яка дозволяє оцінити точність рішення задачі прогнозування запропонованим методом для деякого фіксованого числа відомих значень і компонент векторної послідовності. У роботі також показана блок-схема алгоритму для визначення параметрів запропонованого методу.

УДК 637.522

ДОСЛІДЖЕННЯ МОДЕЛЬНИХ ПАШТЕТНИХ МАС ДЛЯ РОЗРОБЛЕННЯ ТЕХНОЛОГІЇ ФУНКЦІОНАЛЬНИХ ПАШТЕТНИХ ПРОДУКТІВ

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