Regular Algorithm of Adaptive Estimation of the State of a Managed Object with Correlated Noise Object and Interference Measurements

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Abstract — The paper deals with the construction of the regular adaptive estimation algorithms with auto and cross-correlated noise object and interference measurements. In the synthesis of regular estimation algorithms in the case of autoregressive noise and interference measurements of the object describes how to expand the state vector and difference measurements. As a regular procedure uses statistical form discrepancy principle. When constructing regular estimation algorithms in the case of cross-correlated noise and interference measurements of the object as a regularizing procedures used regularization methods M.M.Lavrentev and V.N.Strahov. These expressions allow for convergence of the estimates and to improve the accuracy of their evaluation.

Keywords — Adaptive filtering, correlated noise and interference measurements of the object, regularization, the regularization parameter.

I. INTRODUCTION

In solving various problems of estimation and filtering may be situations where noise and interference measurements of the object are auto-and cross-correlated. In these cases, for random processes due to the time dependence must be considered dynamic transformations, ie transformations, which are described by differential or difference equations.

II. TASK STATEMENT - I

We first consider the algorithms of state estimation of dynamic systems in the presence of autocorrelated noise object and interference measurements. We assume that the system model and measurements are of the form:

\[ x_{i+1} = A_{i+1}i l x_i + \Gamma_{i+1}i l \eta_i, \quad \eta_{i+1} = \tilde{A}_{i+1}i l \eta_i + \tilde{\mu}_i w_{i+1} \]

\[ z_{i+1} = H_{i+1}i l x_{i+1} + \xi_{i+1}, \quad \xi_{i+1} = \tilde{H}_{i+1}i l \xi_i + \tilde{\nu}_i v_{i+1} \]

A priori data set as follows:

\[ w_i \sim N(0, Q_i), \quad v_i \sim N(0, R_i), \]

\[ x_0 \sim N(x_0, P_0), \quad \eta_0 \sim N(\bar{\eta}_0, P^{(\eta)}_0) \]

\[ \text{cov}(x_i, \eta_0) = \text{cov}(x_i, w_i) = \text{cov}(\eta_0, v_i) = 0. \]

Algorithms Of The Decision

Then, following the methods of the theory of optimal filtering and dynamic evaluation [1-4], we can show that the estimation algorithms are given by:

\[ x_{i+1|j+1} = x_{i+1|j} + K_{i+1|j} \times \]

\[ \times \left( z_{i+1} - \tilde{H}_{i+1}j z_j - H_{i+1}j x_{i+1|j} + \tilde{H}_{i+1}j H_{i+1}j x_{i+1|j} \right) \]

\[ x_{i+1|j} = A_{i+1|j}i l x_{i+1|j} + \Gamma_{i+1|j}i l \eta_{i+1|j} \]

\[ \eta_{i+1|j} = \eta_{i+1|j} + K^{(\eta)}_{i+1|j} \times \]

\[ \times \left( z_{i+1} - \tilde{H}_{i+1}j z_j - H_{i+1}j x_{i+1|j} + \tilde{H}_{i+1}j H_{i+1}j x_{i+1|j} \right) \]

\[ P_{i+1}^{(1)} = P_{i+1|j}H_{i+1}j - A_{i+1|j}i l P_{i+1|j}H_{i+1}j \tilde{H}_{i+1}j + \Gamma_{i+1|j}i l W_{i+1|j} \]

\[ P_{i+1}^{(2)} = W_{i+1|j}H_{i+1}j - \tilde{A}_{i+1|j}i l W_{i+1|j}H_{i+1}j \tilde{H}_{i+1}j, \]

\[ \text{cov}(x_i, \eta_i) = W_{j+1} \]

Thus gains \( K_{i+1|j} \) and \( K^{(\eta)}_{i+1|j} \) are determined based on the expressions:

\[ K_{i+1|j} P_{i+1|j}^{(2)} = P_{i+1}^{(1)}, \]

\[ K^{(\eta)}_{i+1|j} P_{i+1|j}^{(2)} = P_{i+1}^{(2)}. \]
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where

\[ P_{i+1}^{(2^i)} = H_{i+1} P_{i+1} H_{i+1}^T - H_{i+1} \left( A_{i+1} P_{i+1} + \Gamma_{i+1} \right) \times \]

\[ \times C_{i+1}^T H_{i+1} H_{i+1}^T + C_{i+1} \Gamma_{i+1}^T H_{i+1} + \]

\[ + \tilde{H}_{i+1} P_{i+1} H_{i+1}^T + B_{i+1} \Gamma_{i+1}^T, \]

\[ P_{i+1} = A_{i+1} P_{i+1} A_{i+1}^T + C_{i+1} \Gamma_{i+1}^T + \]

\[ + \Gamma_{i+1} C_{i+1} A_{i+1}^T + \Gamma_{i+1} D_{i+1} \Gamma_{i+1}^T, \]

\[ P_{i+1|j+1} = P_{i+1} - K_{i+1} P_{i+1}, \]

\[ C_{i+1} = A_{i+1} C_{i+1} A_{i+1}^T + \Gamma_{i+1} D_{i+1} A_{i+1}^T, \]

\[ D_{i+1} = \tilde{A}_{i+1} D_{i+1} \tilde{A}_{i+1}^T + b_{i+1} Q_{i+1} b_{i+1}^T, \]

\[ C_{i+1|j+1} = C_{i+1} - K_{i+1} P_{i+1}^{(2^i)}, \]

\[ D_{i+1|j+1} = D_{i+1} - K_{i+1} P_{i+1}^{(2^i)}, \]

\[ \text{cov} \left( \frac{X_k}{\eta_k} \right) = \left[ \begin{array}{c} P_{j+1} \frac{C_{j+1}}{C_{j+1}^T D_{j+1}^T} \end{array} \right], \quad k = i, i + 1. \]

The method of difference measurement eliminates noise \( v_j \), forming a new dimension \( y_{i+1} \) as a linear combination of two consecutive measurements \( z_i \) and \( z_{i+1} \):

\[ y_{i+1} = z_{i+1} - \tilde{H}_{i+1} z_i. \]  

(12)

Using (10) - (12), we describe a model for measuring:

\[ y_{i+1} = \left( H_{i+1}^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right) x_i^* + \]

\[ + H_i^* b_i^* w_i + \tilde{v}_j v_{i+1}. \]  

(13)

Priori data are given by:

\[ w_i \sim N(0, Q), \quad v_i \sim N(0, R_{i+1}), \]

\[ x_0 \sim N(x_0, P_0), \quad z_0 = 0, \]

\[ \text{cov}(w_i, v_j) = \text{cov}(w_i, x_0) = \text{cov}(v_i, x_0) = 0. \]

For the relations (10) and (13) it is advisable to use a filter-Glonti Lipster [1]. Then:

\[ x_{i+|j+1}^* = x_{i+|j}^* + K_{i+1} \left( y_{i+1} - y_{i+1}^* \right), \]

\[ y_{i+1}^* \begin{bmatrix} x_{i+1}^* \\ y_{i+1}^* \end{bmatrix} = \begin{bmatrix} A_{i+1}^* \\ H_{i+1}^* \end{bmatrix} x_{i+1}^*, \]

\[ K_{i+1} = P_{i+1|j+1} \left( P_{i+1}^{2^i} \right)^{-1}, \]

\[ P_{i+1|j+1} = P_{i+1} - K_{i+1} P_{i+1}, \]

\[ P_{i+1} = A_{i+1} P_{i+1} A_{i+1}^T + b_{i+1} Q_{i+1} b_{i+1}^T, \]

\[ P_{i+1|j+1} = P_{i+1|j+1} \left( H_{i+1}^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right) x_{i+1}^*, \]

\[ P_{i+1} = P_{i+1} \left( H_{i+1}^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right) + b_{i+1} Q_{i+1} b_{i+1}^T, \]

\[ P_{i+1} = P_{i+1} \left( H_{i+1}^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right) + b_{i+1} Q_{i+1} b_{i+1}^T, \]

\[ + H_i^* b_i^* Q_{i+1} \left( H_i^* b_i^* \right)^T + b_{i+1} Q_{i+1} b_{i+1}^T, \]

\[ + \left( H_i^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right) \left( b_{i+1}^* Q_{i+1} b_{i+1} \right)^T + H_i^* b_i^* Q_{i+1} b_{i+1}^T \times \]

\[ \times \left( H_i^* A_{i+1} - \tilde{H}_{i+1} H_i^* \right)^T. \]
Efficiency of estimation algorithms (3) - (7) substantially depends on the accuracy of calculating the gain matrix \( K_{i+1} \) and \( K_{i+1}^{(q)} \) based on the expressions (8) and (9) [1,6]. Matrix \( P_{i+1|j}^{(22)\tau} \) in these expressions may be degenerate or poorly conditioned. To compute \( K_{i+1} \) and \( K_{i+1}^{(q)} \), it is expedient to use a regular procedure [7-11]. Regular algorithm solutions will be considered with respect to the equation (8). The resulting algorithm may also be used in solving equation (9).

Equation (8) can be written as follows:

\[
P_{i+1|j}^{(22)\tau} k_{i+1,j} = p_{i+1,j}^{(1)}, \tag{14}
\]

Where \( k_{i+1,j} \) - j-th column of the matrix \( K_{i+1}^T \), \( j=1,2,...,n \); \( d_{i,j} \) - j-th row of the matrix \( P_{i+1}^{(1)\tau} \), \( j=1,2,...,n \).

In equation (14) the vector elements \( p_{i+1,j}^{(1)} \) known from errors, i.e. instead of \( P_{i+1|j}^{(1)\delta} \) has its random realization \( p_{i+1,j}^{(1)} = p_{i+1,j}^{(1)} + \Delta p_{i+1,j}^{(1)} \). To solve it, we will use the least squares method, whereby estimates of the unknown \( \hat{k}_{i+1,j} \) normal pseudo solution \( k_{i+1,j}^* = (P_{i+1|j}^{(22)\tau})^+ p_{i+1,j}^{(1)} \) system (14) are determined as a solution of \( \inf \| k_{i+1,j} \| \) to

\[
K = \{ k_{i+1,j} : Q k_{i+1,j} = Q_{\text{min}} \} \tag{11,12};
\]

\[
Q_{\text{min}} = \inf_{k_{i+1,j} \in \mathbb{R}^n} Q k_{i+1,j} \]

where

\[
Q k_{i+1,j} = \| P_{i+1|j}^{(22)\tau} k_{i+1,j} - p_{i+1,j}^{(1)\delta} \|^2, \quad \| \cdot \| - \text{Euclidean norm of } (P_{i+1|j}^{(22)\tau})^+ \text{ to } P_{i+1|j}^{(22)\tau} \text{ pseudo-inverse matrix.}
\]

Ratings \( \tilde{k}_{i+1,j} \) are the best in the class of linear unbiased estimators. However, in the case of a degenerate or ill-conditioned matrix of \( P_{i+1|j}^{(22)\tau} \) they are unstable [13], i.e.

\[
M \| \tilde{k}_{i+1,j} \|^2 \gg \| k_{i+1,j}^* \|^2.
\]

Taking into account that the main error of unbiased estimators \( M \| \tilde{k}_{i+1,j} - k_{i+1,j}^* \| \) caused by the displacement of a square length \( \hat{k}_{i+1,j} \), i.e value of \( M \| \tilde{k}_{i+1,j} - k_{i+1,j}^* \|^2 \)

naturally in solving degenerate or ill-conditioned systems of equations of the approximate (8), (9) instead of the class of unbiased estimators consider the class of unbiased estimates with the square of the length, i.e class \( \mathcal{K} = \{ \tilde{k}_{i+1,j} : M \| \tilde{k}_{i+1,j} \|^2 = \| k_{i+1,j}^* \|^2 \} \) ratings. To do this, use the fact [14] that:

\[
MQ_{\text{min}} = (n-l)\sigma^2 < \inf_{k_{i+1,j} \in \mathbb{R}^n} MQ(k_{i+1,j}) = M\| \tilde{k}_{i+1,j} \| = n\sigma^2 \tag{15}
\]

and

\[
M \| \tilde{k}_{i+1,j} \|^2 = \| k_{i+1,j}^* \|^2 + \sigma^2 \text{tr}((P_{i+1|j}^{(22)\tau})^+) \quad \text{where}
\]

\[
Q_{\text{min}} = Q(\tilde{k}_{i+1,j}), \quad l = \text{rank}(P_{i+1|j}^{(22)\tau}).
\]

Inequality (15) shows that using the method of least-squares leads to the "defects" average value of the sum of squared residuals. Natural to require that the regularized estimates eliminate this defect. Then, on the basis of (15) is natural to define the regularized estimates \( \tilde{k}_{i+1,j} \) so as to satisfy the condition:

\[
MQ(\tilde{k}_{i+1,j}) = n\sigma^2. \tag{16}
\]

The parameter \( \alpha \) can be found from the equation residual [11] of the form:

\[
Q(k_{i+1,j}) = Q_{\text{min}} + \delta, \quad \delta > 0. \tag{17}
\]

Then the corresponding regularized estimates of the solutions will be determined from the joint solution of the equations:

\[
P_{i+1|j}^{(22)\tau} k_{i+1,j}^{(a)} + \alpha k_{i+1,j}^{(a)} = p_{i+1|j}^{(1)} \tilde{p}_{i+1,j}^{(1)}, \tag{18}
\]

\[
\| P_{i+1|j}^{(22)\tau} k_{i+1,j}^{(a)} - \tilde{p}_{i+1,j}^{(1)} \|^2 = Q_{\text{min}} + \delta. \tag{19}
\]
To satisfy the conditions (16) the amount of $\delta$ in (17) can be selected based on the ratio $\delta = \delta_0 = l(n-l)^{-1}Q_{\min}$. This is because $M(Q_{\min} + \delta_0) = M[l(n-l)^{-1} \times Q_{\min}] = n\sigma^2$. This method does not require any additional a priori information on an approximate equation system. Following [11,14] we can show that if the condition $\lim_{n \to \infty} n^{-1}P_{ij}^{(22)\scriptscriptstyle{T}} = G > 0$, is satisfied, then $\hat{k}_{\scriptscriptstyle{ij}}^{(opt)}$ and $\hat{k}_{\scriptscriptstyle{ij}}^*$ will be consistent and asymptotically efficient.

In order to select the optimal regularization parameter instead of a class with a non-biased estimates of square of length $K$ we consider the class of regularized estimates $\tilde{K} = \{ k_{\scriptscriptstyle{ij}}^{(y)} \}$.

This class is determined from the Euler equation (18), and the regularization parameter $\alpha$ is determined from the condition of the residual:

$$\| P_{ij}^{(22)\scriptscriptstyle{T}} \delta \|_{\scriptscriptstyle{ij}}^{(\alpha)} - \tilde{P}_{ij}^{(1)} \|_{\scriptscriptstyle{ij}}^{(1)} \|^2 = Q_{\min} + m\sigma^2 + \gamma, \quad (20)$$

It can be shown [11,15,16] that the regularized estimates $k_{\scriptscriptstyle{ij}}^{(y)}$, determined from the equations (18) and (20) satisfy the condition $M \| k_{\scriptscriptstyle{ij}}^{(y)} \|_{\scriptscriptstyle{ij}} \leq \| k_{\scriptscriptstyle{ij}}^* \|_{\scriptscriptstyle{ij}}$. At the same time for optimal regularized estimates $\tilde{k}_{\scriptscriptstyle{ij}}^{(opt)} \neq k_{\scriptscriptstyle{ij}}^*$, and $M(\tilde{P}_{ij}^{(1)} - P_{ij}^{(22)\scriptscriptstyle{T}} \tilde{k}_{\scriptscriptstyle{ij}}^{(opt)}) \neq 0$, which ultimately negatively affect the value of the mean square error estimates of solutions $M \| \tilde{k}_{\scriptscriptstyle{ij}}^{(opt)} - k_{\scriptscriptstyle{ij}}^* \|_{\scriptscriptstyle{ij}}^2$.

To ensure the conditions

$$M \| k_{\scriptscriptstyle{ij}}^{(y)} - k_{\scriptscriptstyle{ij}}^* \|_{\scriptscriptstyle{ij}}^2 \leq M \| k_{\scriptscriptstyle{ij}}^{(opt)} - k_{\scriptscriptstyle{ij}}^* \|_{\scriptscriptstyle{ij}}^2$$

for the choice ($20$) can be found from the condition:

$$\left| \sum_{i=1}^{n} e_{i}^{(\gamma)} \right|_{\gamma} \rightarrow \min, \quad (21)$$

where $e_{i}^{(\gamma)} = (e_{i}^{(\gamma)}^{(1)}, \ldots, e_{i}^{(\gamma)}^{(n)})^T = \tilde{P}_{ij}^{(1)} - P_{ij}^{(22)\scriptscriptstyle{T}} k_{\scriptscriptstyle{ij}}^{(y)}$.

(21) that the parameter $\gamma$ is expedient to choose the form:

$$\gamma_* = \arg \min_{\gamma \in [0, \lim_{n \to \infty} Q_{\min} - m\sigma^2]} \left| \sum_{i=1}^{n} e_{i}^{(\gamma)} \right|.$$
From (29) it follows that the gain matrix $K_i^p$ should be determined on the basis of the expression:

$$K_i^p[G_i R_i] = \Gamma_i C_i.$$  (30)

Thus, the accuracy of the solution during the filtration of correlated noise and interference measurement object substantially depends on the accuracy of $K_i^p$ gain calculation based on equation (30). This system of equations is often ill-conditioned and leads to the application of regularization methods [7,9,10].

For convenience of presentation and brevity we write the equation (30) as follows:

$$L_i k_{i,j} = d_{i,j}^\delta = d_{i,j} + \delta d_{i,j},$$  (31)

Where $L_i = (R_i^T G_i^T)$ - linear operator in a Hilbert space of $H$ to $H$: $k_{i,j}$ - $i$-th row of the matrix $K_i^{pT}$, $j, 1,2,...,n$; $d_{i,j}^\delta$ - $i$-th column of the matrix $D_i = C_i^T I_i^T$ approximation prerequisite form

$$\delta^2 = \|\delta d_{i,j}\|_{E}^2, \quad \delta^2_{\text{max}} < \|\delta d_{i,j}\|_{E} < \delta^2_{\text{max}}, \quad j = 1,2,...,n;$$

$d_{i,j}$ - the exact value of the right-hand side of equation (31).

Consider the case where the operator $L_i$ is self-adjoint and positive. Then M.M.Lavrentev method leads to an equation of the form:

$$ak_{i,j} + L_i k_{i,j} = d_{i,j}^\delta,$$  (32)

Where $\alpha$ - the regularization parameter.

$R_\alpha$ family of operators defined by the formula:

$$R_\alpha = \theta_\alpha (L_i) = (\alpha + L_i)^{-1},$$  (33)

generates a bounded approximation to the problem (31), if the relation $\lim_{\alpha \to 0} R_\alpha L_i k_{i,j} - k_{i,j,1} = 0$, $k_{i,j,1} \perp \ker L_i$,

subject to the conditions of the form:

$$\forall \sup_{\{E_i\}} \theta_\alpha (\lambda) = K_\alpha < \infty, \quad K_\alpha = \alpha^{-1}.$$

$$|\theta_\alpha (\lambda) \lambda^2| \leq c(1 + |\lambda|), \quad |\theta_\alpha (\lambda) \lambda| \leq c(1 + \lambda)$$  [9,10],

where $E_\lambda$ - spectral family of $L_i$, $c$ - constant independent of $\alpha$.

Equation (32) can be expressed in the form of

$$k_{i,j,\alpha} = (\alpha d + \lambda L_i)^{-1} d_{i,j}^\delta = \theta_\alpha (L_i) d_{i,j}^\delta,$$

wherein $\theta_\alpha (\lambda) = (\alpha + \lambda)^{-1}$ - generating system functions $0 \leq \lambda < \infty$ - spectral parameter.

Closer to $k_{i,j,\alpha} = \theta_\alpha (L_i) d_{i,j}^\delta$ pseudo solution equation (30) will be constructed in the form of:

$$k_{i,j,\alpha} = g_\alpha (L_i) d_{i,j}^\delta,$$  (34)

$$\overline{k}_{i,j,\alpha} = \overline{g}_\alpha (L_i) d_{i,j}^\delta,$$  (35)

Approximation (34) and (35) can also be written as

$$k_{i,j,\alpha} = B_\alpha d_{i,j}^\delta,$$

$$\overline{k}_{i,j,\alpha} = \overline{B}_\alpha d_{i,j}^\delta,$$

Where the operators:

$$B_\alpha = g_\alpha (L_i), \quad \overline{B}_\alpha = \overline{g}_\alpha (L_i)$$

approximate $L_i^\lambda$. Then the approximation (34), (35) and (36) take the form:

$$k_{i,j,\alpha} = (L_i + \alpha d)^{-1} d_{i,j}^\delta,$$

$$\overline{k}_{i,j,\alpha} = \overline{B}_\alpha d_{i,j}^\delta,$$

$$B_\alpha = (L_i + \alpha d)^{-1}, \quad \overline{B}_\alpha = \overline{B}_\alpha d_{i,j}^\delta,$$

When implementing the above algorithms regularization parameter $\alpha$ is advisable to determine method based on the discrepancy [7].

If $L_i$ is a self-adjoint operator alternating, then it is advantageous to use the following modification of the method M.M.Lavrentev [17], namely, an approximate solution of the equation $k_{i,j,\alpha}$ (34) determined from the equation:
\[ \mu k_{i,j} + L_i k_{i,j} = d^\delta_{i,j}, \quad \alpha > 0, \quad \mu = \sqrt{-1}. \]  

(37)

Instead of (37) can also use the expression of type

\[ k_{i,j,\alpha} = \text{Re} v_{\alpha}, \quad v_{\alpha} = (i\alpha + L_i)^{-1} d^\delta_{i,j}, \]

or a special computational scheme Tikhonov method:

\[ \alpha^2 k_{i,j,\alpha} + L_i^2 k_{i,j,\alpha} = L_i d^\delta_{i,j}. \]

(38)

On the basis of the results of [18] we can show that for much better conditioning of the system (31) it is advisable to consider a system of the form:

\[ L_{i,\alpha} k_{i,j,\alpha} = \lambda d^\delta_{i,j}, \]

where

\[ L_{i,\alpha} = [(D_L + \alpha D_L^{-1}) + (1 - \beta)(L_i - D_L)], \]

\[ D_L - L_i \text{ diagonal matrix,} \]

\[ \lambda = \lambda_{\alpha} = (d^\delta_{i,j}, L_i \tilde{k}_{i,j,\alpha}) \left( \| L_i \tilde{k}_{i,j,\alpha} \|_E^2 \right)^{-1}, \]

\[ \beta = 1 - \left( \left( D_L + \alpha D_L^{-1} \right)^2 - \| D_L \|_E^2 \left( D_L - L_i \right)^2 \right)^{1/2}, \]

\[ \tilde{k}_{i,j,\alpha} - \text{solution of system } L_{i,\alpha} \tilde{k}_{i,j,\alpha} = d^\delta_{i,j}. \]

Determining the vector \( \tilde{k}_{i,j,\alpha} \) is reduced to the definition of the vector \( \tilde{k}_{i,j,\alpha} \), satisfying the inequality

\[ \| q^\delta_{i,j} - L_i \tilde{k}_{i,j,\alpha} \|_E^2 < \delta^2_{\min}. \]

(39)

Finding \( \tilde{k}_{i,j,\alpha} \) vector associated with the consideration of the set of values of \( \alpha : \alpha_1, \alpha_i = q_i \alpha_{i-1}, \quad l = 2,3,... \), which \( q_i \) are the values that should be in the process of counting. These advantages to determine the magnitude of the formula [18]:

\[ q_i = \left( \delta^2_{\min} / \nu^2_{l-1} \right)^{1/2}, \]

wherein

\[ \nu^2_{l-1} = \| d^\delta_{i,j} - L_i k_{i,j,\alpha_{l-1}} \|_E^2. \]

The value of \( \alpha_i \) can be selected on the basis of the approximate equality of the form

\[ \nu^2_{l-1} = \| d^\delta_{i,j} - L_i k_{i,j,\alpha_l} \|_E^2 \approx \delta^2_{\max}. \]

Subsequent values \( \alpha_i \) should provide a sufficiently rapid determination of the vector \( \tilde{k}_{i,j,\alpha} \), for which

\[ \| d^\delta_{i,j} - \tau_2 L_i \tilde{k}_{i,j,\alpha} \|_E^2 < \delta^2_{\min}, \]

(39)

Defining vector \( \tilde{k}_{i,j,\alpha} \) on the basis of (39), then you can find along the vector \( \tilde{k}_{i,j,\alpha} \) vector \( \hat{k}_{i,j,\alpha} \), satisfying the following two conditions:

\[ \| d^\delta_{i,j} - L_i \hat{k}_{i,j,\alpha} \|_E^2 < \Delta^2, \quad (L_i \hat{k}_{i,j,\alpha}, d^\delta_{i,j} - L_i \hat{k}_{i,j,\alpha}) = 0, \]

Where the \( \Delta^2 = (\delta^2_{\min} + \delta^2_{\max})/2 \). It should be noted here that the values \( \lambda \) and \( \beta \) are based on the selected parameter value \( \alpha \). In this case, \( \beta = \beta_\alpha \) is determined by the principle of conservation of the Euclidean norm of the matrix with its regularization.

IV. CONCLUSION

Thus, the above expression synthesize algorithms for adaptive state estimation of dynamic systems under correlated noise and interference measurements of the object on the basis of approximate methods for solving ill-conditioned or singular stochastic systems of linear algebraic equations, and thus ensure the convergence of the estimates and to improve the accuracy of their evaluation.

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