PARAMETRIC IDENTIFICATION AND DIAGNOSIS OF INTEGRATED NAVIGATION SYSTEMS IN BENCH TEST PROCESS

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Abstract: Growth of complexity and functional importance of integrated navigation systems (INS) leads to high losses at the equipment refusals. The paper is devoted to the INS diagnosis system development, allowing identifying the cause of malfunction. The proposed solutions permit taking into account any changes in sensors dynamic and accuracy characteristics by means of the appropriate error models coefficients. Under actual conditions of INS operation, the determination of current values of the sensor models and estimation filter parameters rely on identification procedures. The results of full-scale experiments are given, which corroborate the expediency of INS error models parametric identification in bench test process.

Keywords: fault detection, integrated navigation systems, state control, sensors, model of errors, parametric identification, supervision, monitoring, fault diagnosis, diagnostic reasoning

ACM Classification Keywords: B.8.1 Reliability, Testing, and Fault-Tolerance; J.2 Computer Applications: Physical Sciences and Engineering: Aerospace

Introduction

Most model-based methods for fault detection and diagnosis rely on the idea of analytical redundancy that is the comparison of the actual behavior of a system to the behavior predicted on the basis of the mathematical system model. Typical model-based fault detection process consists of two steps: residual generation and residual assessing/classification. The decision making is actually a process of classifying the residuals into one of two classes: normal and fault.

Nowadays, the necessity for an inertial support of the operation of integrated navigation systems is considered to be proved. Such a support forms is the basis for the highly maneuverable objects continuous navigational support. However, as for the implementation of the potentialities of inertial navigation systems (INSs), the problem of improving their operational characteristics still remains topical. Among such characteristics which significantly affect the navigational safety we may reckon the INS operational-readiness time, INS accuracy, and INS reliability.

Regarding INSs, traditional approaches [1] to the solution of the above problem rely on the hardware modernization of existing sensors and on the development of new types of sensors such as a gyroscope and an accelerometer. Approaches [1], which involve INS error estimation from data obtained from satellite navigation systems (NSs) and from other external NSs are also deemed to be promising. Furthermore, insufficient attention is given, in our opinion, to the study of the capabilities of combined INSs, built around sensors that are different in the: principle of operation. At the same time, available engineering solutions [2] of such a problem provide the necessary basis in order for studies in this particular field to be conducted.

The evolution of INS relies on improvements both in hardware and in the methods of integrating this hardware. The potentialities of INSs [1] are based on the Kalman filtering technology and on the mathematical INS sensors error models. In order for the INS state to be estimated reliably, the parameters both of models and of an optimal Kalman filter (OKF) must reflect actual measuring processes and noise conditions adequately. Therefore, it is essential that during use of INSs, any changes in noise statistics as well as in dynamic and accuracy sensors characteristics be taken into account. This can be done through the identification and retuning of the appropriate coefficients in an algorithm for data processing.

The potentialities of such a technology make it possible

- to combine dissimilar measurement aids into an integrated structure and to improve the accuracy and reliability of navigational determinations on this basis;
- to implement the mutual support of INSs in the interests of ensuring their integrity;

- to estimate both INS errors and sensor errors from indirect measurements and through the use of correlations;
- to form procedures for the monitoring, diagnosis, and control of the INS technical condition.

However, the effectiveness of OKF application as a kernel of INSs essentially depends on the goodness of fit of the mathematical INS error models and sensor errors to actual measuring processes.

Problem Statement

Generally, the structure of navigating system can be presented in the form of three modules, namely: information sensors, information signal converters from the analogue form into digital and digital processing devices (see figure 1).

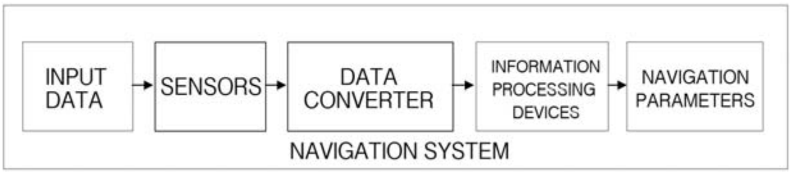

Fig. 1 The structure of typical navigation system

The experience of inertial navigation systems development shows that the intrinsic error of these units defining their functional reliability is the random parametric drift called by dynamically-tuned gyros, interface electronic cards, control cards and couplers. The given task solution is impossible without more profound analysis of occurrence reasons and influence of design and technological parameters on values and stability of random drift.

According to stated, the research of the factors influential in involuntary drift of system and creation of the effective diagnostic technique permitting to estimate current technical condition of INS is the actual task.

The main work purpose is development of algorithms for the INS diagnosis, permitting to reveal reasons of refusals and faults on the data on the basis of structural adapting and navigation model parameters identification.

The offered solution technology includes the following stages:

- the structural adapting of the INS equations in view of the detected disorder and model defect in parametric type;
- retrospective estimation of the extended state INS error vector, originating because of defects;
- correlation processing of the received estimations of errors;
- solution of the algebraic equations on parameters, approximating correlation function and included in diagnostic model;
- INS state handle in view of the current state of meters, namely - retargeting of parameters of error model and INS working capacity restoring.

Given technology will allow solving the following problems:

- optimization malfunctions search strategy;
- separate system units technical condition estimation.

According to the purpose of work it is possible to solve the following research problems:

- the statistical analysis of INS units parameters accuracy not meeting the quality specifications requirements;
- refusals database development of INS interconnected units not past a trial stages;
- open architecture development for processing information from various data sources;
- development realizing automated information capturing for its subsequent processing.
- Parametric Identification of the Error Models of INS Sensors

The full analysis of various methods has led to expediency of application of complex monitoring systems which use different by the physical nature research methods that, in turn, will allow excluding lacks of one method and use advantages of other methods to realize thus a principle of "redundancy" increasing reliability of INS systems.

The integration of navigation systems relies on a priori known models of the errors of sensors, namely, of accelerometers, gyroscopes, pseudorange sensors, and so on. However, when INSs are in use, the sensors characteristics undergo certain changes. This has necessitated taking into account these changes through the models of errors of the sensors. Thus, the problem of identifying the models of sensor errors parameters arises. The above problem can be solved on the basis of correlative processing of the estimates of sensor errors both in real time and in the postprocessing INS diagnosis.

The equations describing INS functioning in an operating mode can be represented in a general view

$$\dot{y}(t) = F(y,t); \tag{1}$$

$$\dot{y}_p(t) = F(y_p,t) + G(t)\xi(t), \tag{2}$$

where $y(t)$ – n-dimensional state parameter vector of ideal (undisturbed) INS;

$y_p(t)$ – n-dimensional state parameter vector of real (disturbed) INS;

$F(y_p,t)$ – vector function;

$\xi(t)$ – r-dimensional INS disturbance vector;

$G(t)$ – link coefficient matrix of $\xi(t)$ vector with $y_p(t)$ vector ($n \times q$ matrix of variable coefficients describing the INS sensors noise intensity).

The following INS error equation could be put in conformity to the correlations (1) and (2):

$$x(t) = A(t)x(t) + G(t)\xi(t); \tag{3}$$

where $x(t)=y_p(t)-y(t)$ - INS error vector (n-dimensional INS disturbed vector parameters deviation from undisturbed INS vector parameters);

$$A(t) = \frac{\partial F(y,t)}{\partial y}\bigg|_{y = y_{P(i)}} \text{ - } n \times n \text{ partial derivative matrix.} \tag{4}$$

In the onboard implementation of the models of INS errors, it is deemed possible to have an approximate description of the gyro random drift and the accelerometer random displacement as the Markov Gaussian first-order process

$$\Delta \dot{\mu} = -\frac{1}{\tau_\mu}\Delta\mu + \xi\sigma_\mu\sqrt{\frac{2}{\tau_\mu}} \tag{5}$$

with the exponential correlation function

$$R_\mu(t) = \sigma^2{}_\mu e^{-\alpha_\mu|t|}, \tag{6}$$

where t – running time, $\alpha_\mu = {}^1\!/_{\tau_\mu}$; τ_μ is the correlation time; $R(0) = \sigma^2{}_\mu$ is the error variance; σ – mean-square deviation of random error; $\xi \in N(0,1)$; μ – sensor related index ($\mu = a$ – accelerometer; $\mu = \omega$ – gyroscope).

Taking into account $A_\mu = \tau_\mu{}^{-1}$; $G_\mu = \sigma_\mu\sqrt{{}^2\!/_{\tau_\mu}}$ the equation (5) could be embedded in general structure INS error equation (3).

In the equations, coefficients A_μ, G_μ are a priori defined for sensor nonfault states. The change in the technical condition of sensors during use of INSs has an influence both on the parameters and on the structure of the models of errors. Therefore, the need arises for refinement of the models during bench tests. For this purpose, we propose that the technology of structural parametric identification of the models should be used. Such a technology is based on the requirement that the base models of sensor errors be in agreement with the results of correlative processing of estimates in real time. Provision is made for the extension of the sensor errors models, which is adequate to the form of correlation functions when the postprocessing of bench test data is performed.

In relations (1) and (2), the quantity α_μ is the parameter that is to be identified. In this case, the problem can be reduced to the finding of the α_μ value, which minimizes the quadratic function

$$\hat{\alpha}_\mu = \operatorname{argmin} \sum_{j=1}^{N} (\hat{R}_{\mu j} - \sigma_\mu^2 \, e^{-\alpha_\mu \tau_j})^2 , \tag{8}$$

where $\hat{R}_{\mu j}$ is the correlation function that is determined from experimental data in the following way:

$$\hat{R}_k = \frac{1}{N} \sum_{i=k+1}^{N+k} \overset{\circ}{x}_i \, \overset{\circ}{x}_{i-k} \quad , \; k = \overline{0, N} \, ; \; \overset{\circ}{x}_i = x_i - m_x \, ; \quad m_x = \frac{1}{N} \sum_{i=1}^{N} x_i \; , \tag{9}$$

where $x_i = x(t_i)$ – estimated error of corresponding sensor; N –number of retrospective counts;

$$\tau_j = j\Delta t_i \, ; \; \Delta t_i = t_i - t_{i-1} \, ,$$

t_i – discrete instants of time.

As for NSs, the present state of their hardware support and mathematical-and-software support makes it possible to extend the field of application of the methods of integrated data processing by "entrusting" these methods with the solution of unconventional problems. Among such problems we may reckon monitoring, diagnosis, identification, and estimation of the NS technical condition from bench tests data.

A traditional estimation scheme is an open-loop one intended to compensate for the estimates of INS errors; this scheme is shown in fig. 2, where the following notation is introduced: y_{DS} is the vector of parameters that are reckoned by the INS; y_{EIS} is the vector of parameters that are reckoned by the external information sensors; z is the vector of observations; $\hat{x}$ is the vector of estimates of INS errors, $\omega(t)$ - dynamic system disturbance vector; $\vartheta(t)$ - disturbance vector in observation channel.

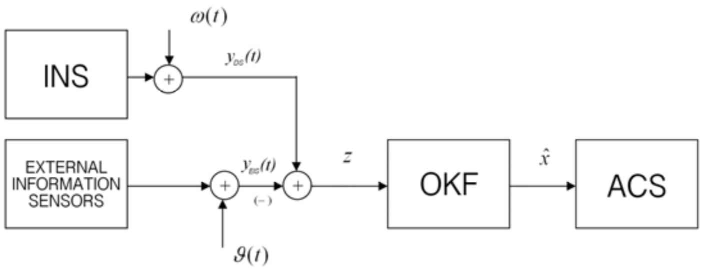

Fig. 2 Open-loop scheme for the damping of INS errors

Using inertial navigation signals and external navigation sensors observations, pseudoranges and velocities measurements the INS error vector estimation could be performed in the following way:

$$z_k = [\varphi \lambda \overline{V}]^T{}_{INS} - [\varphi \lambda \overline{V}]^T{}_{EIS} \tag{7}$$

In the equation (7): φ, λ – geographic latitude and longitude location of moving object; $\overline{V}$ – relative velocity vector of moving object.

Functional monitoring of integrated NSs relies on the technique of channel-wise (element-wise) processing of the vector $z_i = \{z_1,...,z_l\}$ of observations. Based on such a technique, it is apparently possible to check an NS by means of generalized parameters that characterize the state of each of the l measuring channels. For instance, in order to check the j-th measuring channel, use can be made of the normalized residual $\beta_j = \nu_j / \alpha_j$, where α_j is a scaling parameter; $j = \overline{1, l}$; l is the dimensionality of the vector z_i of observations. When observations are processed in "forward" time, the residual ν_j is the difference $\nu_j = z_j - \hat{z}_j$ in value between the actual observation z_j and the predicted observation $\hat{z}_j = H_j \hat{m}_j$, where m_j, $\hat{x}_{i/i}$ is the estimate of the NS error vector x_i at the i-th step after the j-th component and the whole of the vector z_i of observations are processed, respectively; H_j is the row vector of coupling coefficients. Statistical properties of the above-mentioned residuals can be used for the construction of decision rules.

As is known [4] in the absence of discrepancy between the predicted and real observation, the square of the normalized residual β_j^2 is distributed as χ^2, and the quotient of the actual variance $\hat{\alpha}_j^2$ and the predicted variance α_j^2 has the ϑ^2 distribution.

For the distributions in question, the mathematical expectation and variance have tabulated values. These can be used for the formation of tolerances and for the classification of the types of technical condition of an integrated navigation system [5], i.e., of the good condition, operable condition, etc.

Necessary conditions for the good state of the integrated navigation system in reference to the j-th component z_i of the vector of observations follow from the properties of the residual ν_j, and they have the form

$$\nu_j \in N(0,\alpha^2); \qquad \beta_j^2 = \nu_j^2 / \alpha_j^2 \in \chi^2(1,2); \qquad F_j = \hat{\alpha}_j^2 / \alpha_j^2 \in \vartheta(a,b),$$

whereby $\hat{\alpha}_j^2$ is a true value of the variance of the j-th residual, computed on a moving time interval; *a, b* are the tabulated values of the mathematical expectation and variance for the ϑ^2 distribution.

Using the "three-sigma rule" as well as the properties of the χ^2 and ϑ^2 distributions, one can form the tolerances γ_j^2 and η_j^2 respectively on the good and operable condition of the integrated NS in reference to the j-th vector of observations channel, i.e.,

$$\beta_j^2 \le \gamma^2 = 1 + 3\sqrt{2} \approx 5.2; \qquad F_j \le \eta^2 = a + 3\sqrt{2b}.$$

The parameter β_j^2 is formed using the current residual and it reflects the current status of j-th channel of the vector of observations. If it is out of the tolerance γ^2, this fact may be associated both with outliers and with failures. The parameter F_j is the quotient of the actual and predicted variance of the residual. It is formed over an averaged range of values of the residual on a moving time interval. Therefore, if it is out of the tolerance η^2, this fact may be associated with a gradual failure.

The above method intended for the estimation and functional monitoring permits one to establish only the fact that there is a discrepancy between the output signals of the NSs being united, and this fact manifests itself by means of the appropriate components of the vector of the residuals ν_i. Because of this, in order for the diagnosis to be performed, it is apparently expedient to make use of generalized parameters such that the discrepancy would be ascertained for each component of the state vector of an integrated navigation system. In what follows, we show that in order to localize a trouble for the depth of a sensor, namely, of an accelerometer, a gyroscope, it is possible to use some of the combinations of estimates that were obtained in the processing of observations in "forward" and "backward" time.

Analysis of the Results of Studies

The INS-2000 integrated inertial satellite navigation system [3], developed by the RDC (Ramenskoye) has been the object of experimental studies. One of the experiments has been carried out using a bench set of the INS-2000 system, mounted on a geodetically tied-in rotary table. The rotary table was considered as a reference base intended for determination of the actual phase path. The Poisson algorithm for the reckoning of the geographical position from direction cosines and of the projections of the vector of relative velocity on the axes of an inertial measurement unit (IMU) is a navigational kernel of the INS. The basic state vector was comprised of 18 parameters, namely: errors of the IMU angular position; errors in the reckoning of the components of the vector of relative velocity in the direction of the IMU axes; errors in the reckoning of direction cosines; IMU angular drifts and displacements of accelerometers. The results of INS state estimation are shown on fig. 3

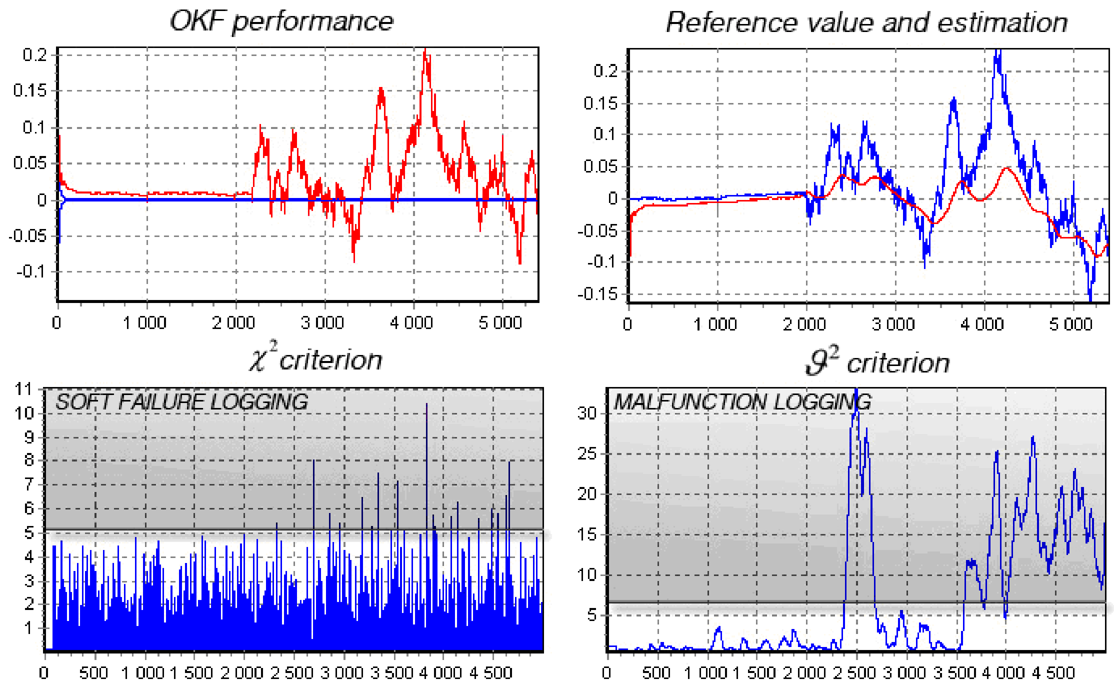

Fig. 3 Results INS state estimation and malfunction logging

Conclusion

In the paper presented here, the authors draw your attention to the importance of systems approach to the construction of mathematical and software support for integrated navigation systems (INSs). Such an approach enables us to combine the capabilities of algorithmic and hardware means intended to improve the accuracy and reliability of INSs. The algorithms considered can form a basis in the construction of a unified technological process, meant for estimation, identification, and control of the INS state. The unified technological process implementation is of great importance in the creation of INSs that provide safety in the use of moving objects.

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