Metrol. Meas. Syst., Vol. 24 (2017), No. 2, pp. 347–356.

METROLOGY AND MEASUREMENT SYSTEMS

Index 330930, ISSN 0860-8229

www.metrology.pg.gda.pl

NOVEL VARIABLE STRUCTURE MEASUREMENT SYSTEM WITH INTELLIGENT COMPONENTS FOR FLIGHT VEHICLES

Kai Shen[1,2], Maria S. Selezneva[2], Konstantin A. Neusypin[2], Andrey V. Proletarsky[2]

1) Nanjing University of Science and Technology, School of Mechanical Engineering, Nanjing, 210094, P.R. China (✉ shenkaichn@mail.ru, +8 925 373 8978*)*

2) Bauman Moscow State Technical University, Faculty of Computer Science and Control Systems, Moscow, 105005, Russia (m.s.selezneva@mail.ru, neysipin@mail.ru, pav_mipk@mail.ru)

Abstract

The paper presents a method of developing a variable structure measurement system with intelligent components for flight vehicles. In order to find a distinguishing feature of a variable structure, a numerical criterion for selecting measuring sensors is proposed by quantifying the observability of different states of the system. Based on the Peter K. Anokhin's theory of functional systems, a mechanism of "action acceptor" is built with intelligent components, *e.g.* self-organization algorithms. In this mechanism, firstly, prediction models of system states are constructed using self-organization algorithms; secondly, the predicted and measured values are compared; thirdly, an optimal structure of the measurement system is finally determined based on the results of comparison. According to the results of simulation with practical data and experiments obtained during field tests, the novel developed measurement system has the properties of high-accuracy, reliable operation and fault tolerance.

Keywords: flight vehicle, variable structure measurement system, the degree of observability, self-organization algorithm, integrated navigation system.

1. Introduction

Vehicles that are capable of sustained motion through air and space are termed as *flight vehicles* (FV), and they are generally classified as aircrafts, space-crafts and rockets. All flight vehicles require manipulation (*i.e.* control or adjustment) of their position, velocity and orientation for efficient completion of flight missions based upon the measurement information about operation states [1]. However, in practice the measurement information is usually disturbed by internal and external noise. Thus, in order to improve accuracy of on-board measurement systems, a novel design scheme is developed with intelligent components based on the Peter K. Anokhin's functional system theory [2, 3].

As we all know, on-board measurement systems usually consist of an *inertial navigation system* (INS), a *global navigation satellite system* (GNSS), a *ground-based radio navigation system* (GRNS), a *terrain-referenced navigation system* (TRNS), a *continuous visual navigation system* (CVNS) *etc*. [4]. The above mentioned systems are generally integrated using Kalman filtering [4, 5] to fuse navigation information with different characteristics. However, the operability of those sensors varies all the time with changes of external environment. For example, when our flight vehicles are working in a battlefield environment, it may be impossible to access the position, navigation, and *timing* (PNT) information with ordinary GNSS receivers. Therefore, the novel measurement system presented in this paper is designed with a variable structure. To achieve this goal, some selection criteria of measurement information, *e.g.* a numerical criterion of the *degree of observability* (DoO), must be formulated for time-varying conditions.

Article history: received on Nov. 19, 2016; accepted on Jan. 14, 2017; available online on Jun. 30, 2017; DOI: 10.1515/mms-2017-0025.

In addition, according to the Peter K. Anokhin functional system theory, a mechanism of "acceptor of the results of action" [2] (or just "action acceptor") is necessary for our new developed measurement system, because it can help us to select an optimal combination of measuring sensors and to determine a better measurement structure for a current working period. To introduce this mechanism, *self-organization algorithms* (SOA) [6] functioning as an intelligent component are suggested to be put into use.

The paper is organized as follows. In Section 2, a methodology of quantitative observability analysis with the degree of observability, functioning as a kind of selection criterion of measurement information, is introduced for *linear time-varying* (LTV) systems. In Section 3, self-organization algorithms used for constructing prediction models are briefly examined. In Section 4, an analytical methodology for optimizing system parameters and modelling in synthesis of a measurement system is presented. In Section 5, a novel measurement system is developed on the basis of the Peter K. Anokhin's functional system theory. In order to clearly demonstrate performance and effectiveness of the proposed measurement system, the results of simulation using practical data and field test results are presented.

2. Measurement selection criterion and degree of observability

In this section, we are interested in finding a figure of merit for each state-variable that can reflect how observable the state-variable is. A criterion having this function may be termed the numerical criterion of the degree of observability. Moreover, the degree of observability can further serve as an indicator in selecting better measuring sensors for a current working period in formulating variable structure measurement systems [1]. As we have mentioned above, the external environment and internal system states are continuously changing in time. Therefore, the system of interest is commonly expressed as a linear time-varying system:

$$\mathbf{x}_k = \mathbf{F}_{k,k-1}\mathbf{x}_{k-1} + \mathbf{w}_{k-1}, \tag{1}$$

$$\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k, \tag{2}$$

where $\mathbf{x}_k$ is a vector of state; $\mathbf{w}_{k-1}$ is a vector of input noise; $\mathbf{z}_k$ is a vector of measurement; $\mathbf{v}_k$ is a vector of measurement noise; $\mathbf{F}_{k,k-1}$ is a state transfer matrix; $\mathbf{H}_k$ is a measurement matrix.

We assume that the input $\mathbf{w}_{k-1}$ and measurement $\mathbf{v}_k$ noise is the white Gaussian noise, and there is no evident correlation between them, *i.e.* $E\left[\mathbf{v}_j\mathbf{w}_k^T\right] = 0$ for any j and k.

In respect to the system represented by (1) and (2), a measurement $\mathbf{z}_k$ may be reformulated as follows [7]:

$$\begin{aligned}
\mathbf{z}_k &= \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k \\
\mathbf{z}_{k+1} &= \mathbf{H}_{k+1}\mathbf{F}_{k+1,k}\mathbf{x}_k + \mathbf{H}_{k+1}\mathbf{w}_k + \mathbf{v}_{k+1} \\
&\cdots \qquad \cdots \qquad \cdots \\
\mathbf{z}_{k+n-1} &= \mathbf{H}_{k+n-1}\mathbf{F}_{k+n-1,k+n-2}\cdots\mathbf{F}_{k+1,k}\mathbf{x}_k + \mathbf{H}_{k+n-1}\mathbf{F}_{k+n-1,k+n-2}\cdots\mathbf{F}_{k+2,k+1}\mathbf{w}_k \\
&\quad + \cdots + \mathbf{H}_{k+n-1}\mathbf{w}_{k+n-2} + \mathbf{v}_{k+n-1},
\end{aligned} \tag{3}$$

where n is the order of the system.

Then, we can rewrite the expression (3) in a matrix form as:

$$\mathbf{z}_k^* = \mathbf{O}_k\mathbf{x}_k + \mathbf{v}_k^*, \tag{4}$$

where $\mathbf{z}_k^* = \begin{bmatrix} \mathbf{z}_k \\ \mathbf{z}_{k+1} \\ \cdots \\ \mathbf{z}_{k+n-1} \end{bmatrix}$, $\mathbf{O}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_{k+1}\mathbf{F}_{k+1,k} \\ \cdots \\ \mathbf{H}_{k+n-1}\mathbf{F}_{k+n-1,k+n-2}\cdots\mathbf{F}_{k+1,k} \end{bmatrix}$;

$$\mathbf{v}_k^* = \begin{bmatrix} \mathbf{v}_k^+ \\ \mathbf{v}_{k+1}^+ \\ \cdots \\ \mathbf{v}_{k+n-1}^+ \end{bmatrix} = \begin{bmatrix} \mathbf{v}_k \\ \mathbf{H}_{k+1}\mathbf{w}_k + \mathbf{v}_{k+1} \\ \cdots \quad \cdots \quad \cdots \\ \mathbf{H}_{k+n-1}\mathbf{F}_{k+n-1,k+n-2}\cdots\mathbf{F}_{k+2,k+1}\mathbf{w}_k + \cdots + \mathbf{H}_{k+n-1}\mathbf{w}_{k+n-2} + \mathbf{v}_{k+n-1} \end{bmatrix}.$$

A matrix $\mathbf{O}_k$ is termed the local observability matrix of an LTV system [8]. To examine the local observability over a period from k to $k+n-1$, we can use as the observability rank criterion being the local observability matrix $\mathbf{O}_k$ of rank n for the period, *i.e.*

$$rank\{\mathbf{O}_k\} = n. \tag{5}$$

Considering (4), we can step by step obtain a relationship of state-variables and measurement as:

$$\mathbf{O}_k^T\mathbf{z}_k^* = \mathbf{O}_k^T\mathbf{O}_k\mathbf{x}_k + \mathbf{O}_k^T\mathbf{v}_k^*, \tag{6}$$

or

$$\mathbf{O}_k^T\mathbf{O}_k\mathbf{x}_k = \mathbf{O}_k^T\mathbf{z}_k^* - \mathbf{O}_k^T\mathbf{v}_k^*, \tag{7}$$

then

$$\mathbf{x}_k = \left[\mathbf{O}_k^T\mathbf{O}_k\right]^{-1}\mathbf{O}_k^T\mathbf{z}_k^* - \left[\mathbf{O}_k^T\mathbf{O}_k\right]^{-1}\mathbf{O}_k^T\mathbf{v}_k^*, \tag{8}$$

and finally

$$\mathbf{x}_k = \mathbf{O}_k^\dagger\mathbf{z}_k^* - \mathbf{O}_k^\dagger\mathbf{v}_k^*, \tag{9}$$

where † means the Moore-Penrose pseudoinverse of matrix.

Let $\mathbf{y}_k = \mathbf{O}_k^\dagger\mathbf{z}_k^*$, considering (4), we can obtain a scalar form of vector $\mathbf{y}_k$ as:

$$y_k^i = a_{1,k}^i z_k + a_{2,k}^i z_{k+1} + \cdots + a_{n,k}^i z_{k+n-1}, \tag{10}$$

where y_k^i is the *i*-th component of vector $\mathbf{y}_k$, $a_{j,k}^i (j = 1,\cdots,n)$ are time-varying elements of the *i*-th row in the matrix $\mathbf{O}_k^\dagger$.

Correspondingly, the measurement noise $\boldsymbol{\varsigma}_k^* = \mathbf{O}_k^\dagger\mathbf{v}_k^*$ in a scalar form is:

$$\varsigma_k^{*i} = a_{1,k}^i v_k^+ + a_{2,k}^i v_{k+1}^+ + \cdots + a_{n,k}^i v_{k+n-1}^+, \tag{11}$$

where ς_k^{*i} is the *i*-th component of vector $\boldsymbol{\varsigma}_k^*$.

Furthermore, the variance of measurement noise ς_k^{*i} may be expressed as:

$$R_k^{*i} = \left[\left(a_{1,k}^i\right)^2 + \left(a_{2,k}^i\right)^2 + \cdots + \left(a_{n,k}^i\right)^2\right]R_k^+, \tag{12}$$

where R_k^+ is the variance of direct measurement noise v_k^+.

Therefore, the degree of observability for an LTV system can be defined as [7]:

$$D_k^i = \frac{E\left[\left(x^i\right)^2\right]R_k^+}{E\left[\left(y^i\right)^2\right]R_k^{*i}}. \tag{13}$$

From (12), we know that the ratio of the variance values of measurement noise is $\sum_{j=1}^{n}\left(a_{j,k}^{i}\right)^{2}$, thus we can rewrite (13) and finally obtain:

$$D_k^i = \frac{E\left[\left(x^i\right)^2\right]}{E\left[\left(y^i\right)^2\right]\sum_{j=1}^{n}\left(a_{j,k}^{i}\right)^{2}}. \tag{14}$$

In practice, $E\left[\left(x^i\right)^2\right]$ and $E\left[\left(y^i\right)^2\right]$ in (14) are usually calculated as:

$$E\left[\left(x^i\right)^2\right] = \frac{1}{n}\sum_{l=k}^{k+n-1}\left(x_l^i\right)^2, \tag{15}$$

$$E\left[\left(y^i\right)^2\right] = \frac{1}{n}\sum_{l=k}^{k+n-1}\left(y_l^i\right)^2. \tag{16}$$

It is apparent from (14) that the system parameters in the matrix $\mathbf{F}_{k,k-1}$ have an indirect influence on the degree of observability by the elements $a_{j,k}^{i}\,(j=1,\cdots,n)$ in the pseudoinverse matrix of observability $\mathbf{O}_k^{\dagger}$. In practical applications, this feature makes it possible to optimize physical model parameters and to determine optimal variable structures for measurement systems.

3. Algorithms for constructing prediction models

In order to guarantee high-precision selection and fusion of information, the mechanism of "action acceptor" is necessary in our novel variable structure measurement systems. In this mechanism, except for the application of the degree of observability, algorithms for constructing prediction models are also required for further comparing the a posteriori and predicted information. From the results of comparison [2, 9], an optimal structure of the measurement system can be finally determined for the current working period in accordance with the operation conditions of flight vehicles. In this section, we shall introduce some algorithms, *e.g.* self-organization algorithms, for constructing mathematical prediction models.

In general, we define a mathematical prediction model as:

$$M_k = \sum_{i=1}^{L} a_i \mu_i\left(f_i, x_k\right), \tag{17}$$

where μ_i is a basic function from the function set F_s $\left(F_s = \left\{a_i\mu_i\left(f_i, x_k\right) \mid i = 1,\cdots,L\right\}\right)$ and a_i is an amplitude, f_i is a frequency, L is the number of basic functions.

As the basic functions, we usually select three types of functions to build mathematical prediction models owing to the dynamic features of flight vehicles.

a) A linear trend (function) has a form:

$$\hat{x}_k^L\left(a_l, b_l\right) = k_k^l t_k + d_k^l, \tag{18}$$

where $\hat{x}_k^L$ is a predicted value, k_k^l, d_k^l are a slope and a constant of the linear function, a_l, b_l are coordinates of the reference point.

b) A nonlinear harmonic trend (function) is:

$$\hat{x}_k^N = A_k \sin\left(\omega_k^s t_k + \varphi_k^s\right) + B_k \cos\left(\omega_k^c t_k + \varphi_k^c\right), \tag{19}$$

where $\hat{x}_k^N$ is a predicted value, $A_k, B_k, \omega_k^s, \omega_k^c, \varphi_k^s, \varphi_k^c$ are amplitudes, frequencies and phases of the trigonometric functions.

c) A Modified Demark trend is expressed as:

$$\hat{x}_k^D = \hat{x}_{k-1}^D + C_{k-1}, \tag{20}$$

where $\hat{x}_k^D$ is a predicted value and

$$C_{k-1} = \zeta_{k-1}^L \hat{x}_{k-1}^L + \zeta_{k-1}^N \hat{x}_{k-1}^N, \tag{21}$$

where $\zeta_{k-1}^L, \zeta_{k-1}^N$ are weighing factors within a range from 0 to 1.

In order to find an optimal solution χ_j for mathematical prediction models, we would like to introduce a quadratic criterion [10] with respect to the amplitude a_i as:

$$\sum_{j=k}^{k+n-1} \left[-2\chi_j \mu_i \left(f_i, x_j \right) + 2a_i \mu_i^2 \left(f_i, x_j \right) \right] = 0 . \tag{22}$$

Then, we may differentiate it by the amplitude a_i and obtain:

$$a_i = \frac{\sum_{j=k}^{k+n-1} \chi_j \mu_i \left(f_i, x_j \right)}{\sum_{j=k}^{k+n-1} \mu_i^2 \left(f_i, x_j \right)} . \tag{23}$$

With (23) we can easily find a good optimal solution of prediction models based on the self-organization selection criteria [6]:

a) the minimum deviation criterion:

$$\Delta_M^2 = \frac{\sum_{i=1}^{L} \left(\hat{x}_i^P - \hat{x}_i^Q \right)^2}{\sum_{i=1}^{L} z_i^2} \to \min, \tag{24}$$

where $\hat{x}_i^P$ and $\hat{x}_i^Q$ designate two parts of a predicted value, z_i is a measurement value.

b) the regularity criterion:

$$\Delta_R^2 = \frac{\sum_{i=1}^{L} \left(z_i - \hat{x}_i \right)^2}{\sum_{i=1}^{L} z_i^2} \to \min , \tag{25}$$

where $\hat{x}_i$ is a predicted value.

Based on the above-mentioned basic functions (18) – (20), we can thus build some self-organization algorithms by utilizing the self-organization selection criteria (24) and (25). One of the most effective algorithms is a so-called self-organization algorithm with redundant trends, as shown in Fig. 1, where SC are selection criteria, C are competitive prediction models.

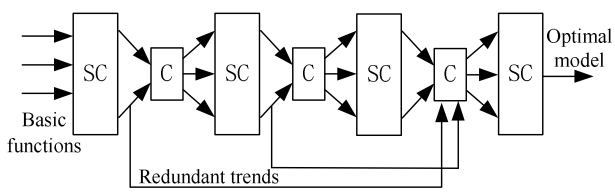

Fig. 1. A functional scheme of self-organization algorithm with redundant trends.

Similarly, evolutionary algorithms, *e.g.* genetic algorithms and neural networks, can also function as tools for building prediction models. Eventually, we can obtain an optimal mathematical prediction model using the above proposed algorithms.

4. Analytical methodology for optimizing system parameters and modelling

On the basis of the concept of measurement system synthesis [1, 9], it is necessary to rationally reduce the number of model parameters of the system. For this purpose, we would like to introduce a practical methodology for optimizing system parameters in accordance with the external and internal changes.

In the practical implementation of parameter optimization, we can simply divide the system parameters into three types considering the changing rates of parameter values. For example, all the system parameters are classified as “slow”, “normal” and “fast” variables. Correspondingly, during processing the measurement information in practice, we may make some modifications, as follows: slow changing parameters are replaced with constants; fast changing parameters are replaced with their average values. Next, according to the problem statement, the clarification (or correction) of variables is made. As a result, an hierarchy diagram of optimizing system parameters considering their changing rates is formulated, as shown in Fig. 2.

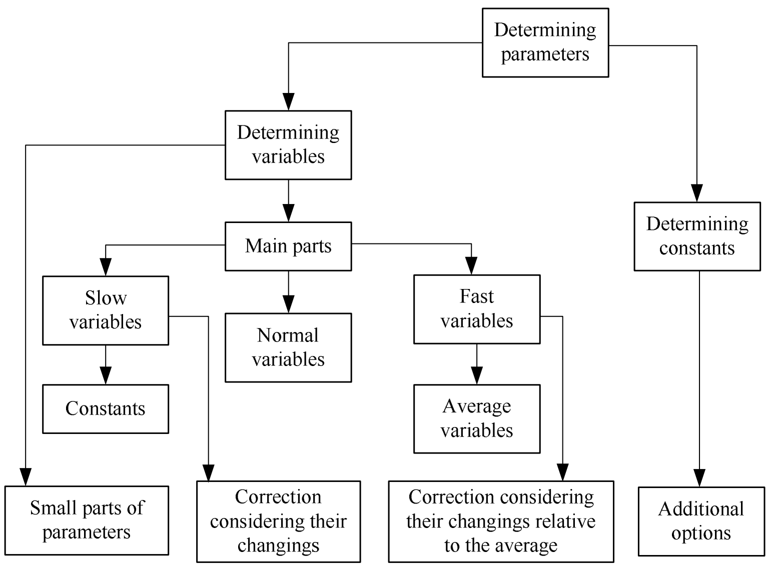

Fig. 2. An hierarchy diagram of optimizing system parameters considering their changing rates.

The presented hierarchy method of optimizing system parameters can be applied in the mechanism of “action acceptor” to building measurement systems with intelligent components.

In respect to the modelling optimization with optimizing parameters, based on the theory of system synthesis [9], a novel practical methodology for modelling is developed by adopting the numerical criteria of the degree of observability and the criteria of self-organization selection. A functional diagram of modelling in measurement systems with intelligent components is presented in Fig. 3.

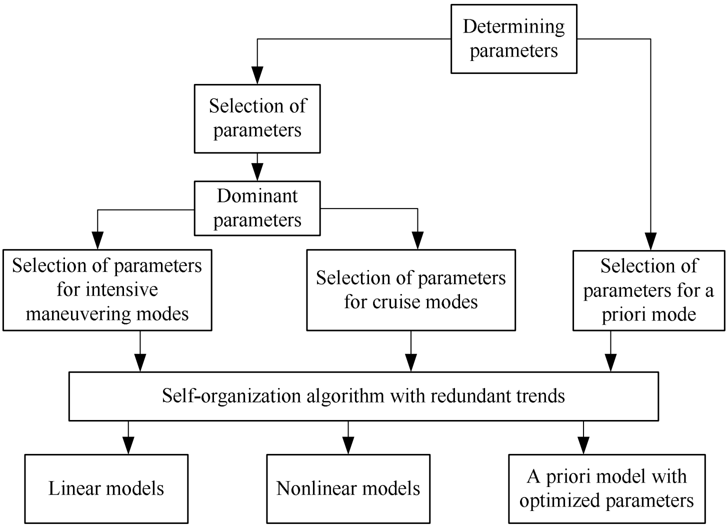

Fig. 3. A functional diagram of modelling in measurement systems with intelligent components.

In Fig. 3, dominant parameters are selected using the criterion of the degree of observability with a low threshold. Furthermore, different types of models are formulated depending on the operation modes of flight vehicles. However, it should be noted that for intensive manoeuvring modes a high threshold value of the degree of observability is further suggested to be used to guarantee effective information processing and high accuracy of parameter determination.

In this section, we examine the analytical methodology for optimizing system parameters and modelling, and illustrate practical techniques by their functional diagrams. According to the above proposed design concepts, the novel developed measurement system structure is guaranteed to be compact, which is beneficial in practical applications.

5. Variable structure measurement system with intelligent components

Rapid development of cybernetics, computer engineering, biotechnology and artificial intelligence leads to the appearance of measurement systems with intelligent components. Based on the systematic synthesis concept and the Peter K. Anokhin's functional system theory [1, 3], in this section we present a new type of measurement system with a variable structure and show its working principles as well as practical advantages.

As we all know, the operation environments (external and internal) of flight vehicles are constantly changing. Thus, a variable structure of the measurement system should be designed to adapt to those changes. In order to do that, the degree of observability must be used as an automatic selection criterion (or indicator) of measurement information. Except for that, the mechanism of "action acceptor", consisting of a *block of information fusion and selection* (BIFS), an *algorithm for constructing models* (ACM) and a *block of prediction algorithms* (BPA), also needs to be formulated.

Based on the above-mentioned numerical criterion of the degree of observability, self-organization algorithms and other practical methodologies, a novel variable structure measurement system with intelligent components has been developed, as shown in Fig. 4, where Sensor 1 is the basic navigation sensor (*e.g.* an inertial navigation system), Sensors 2 – N are external supporting navigation systems (*e.g.* GNSS, TRNS, CVNS, and so on) [4, 11, 12], BEA is a block of estimation algorithms (*e.g.* Kalman filtering [5, 13]), θ is actual navigation information, x is a navigation error, z is measurement information, $\hat{x}$ is an estimate, $\hat{\hat{x}}$ is a predicted value, $\tilde{x}$ is an estimation error.

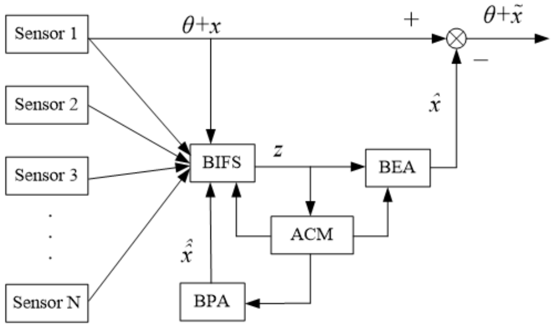

Fig. 4. A functional scheme of a novel variable structure measurement system with intelligent components.

In the block of information fusion and selection, the optimal structure of measurement system is determined by comparing the measured and predicted information on the basis of the degree of observability. With the changes of external and internal conditions, the structure of measurement systems is always in the process of change. Therefore, this process is similar to an intelligent decision-making procedure and thus guarantees the optimization of the system structure.

In order to comprehensively explain the working principles of the proposed novel measurement system, we carried out simulations with the use of practical data. To measure the position and velocity of our flight vehicles, we used GNSS receivers, TRNS and CVNS cameras. Accordingly, the degrees of observability of velocity errors obtained by using different measuring sensors were calculated, as shown in Fig. 5.

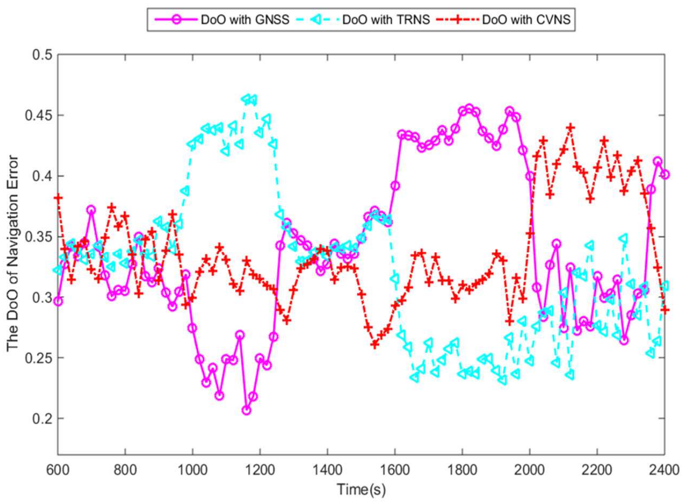

Fig. 5. The degrees of observability of navigation errors obtained by different sensors.

Figure 5 clearly shows the variant trend and the percentage of having the degree of observability for different navigation sensors. The results are advantageous in calculation of information-sharing factors during the information fusion [13, 14]. In addition, the calculated degree of observability can serve as an indicator in selection of better external supporting navigation systems for a current working period.

On the basis of the above results, it is easy to decide which of the supporting sensors should be selected during a current period and how to change or optimize the structure of the measurement system in order to adapt to the changes of internal states and external conditions.

Moreover, the field tests were also carried out in a semi-real environment. During the tests, we set a change period of the measurement structure equal to 20 seconds taking into account the practical requirement and on-board computation capability. The test results are shown in Fig. 6.

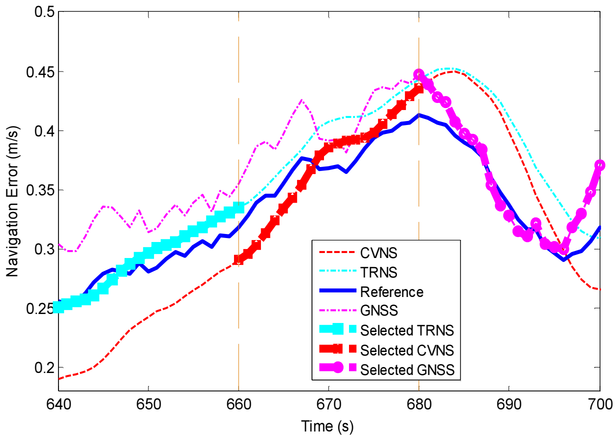

Fig. 6. The field test results of the novel developed variable structure measurement system.

As shown in Fig. 6, based on analysis of the observability, a combination of basic INS and supporting TRNS worked with a better accuracy than that of other measurement functional structures in an interval from 640 to 660 sec. Thus, in order to obtain an optimal measurement structure, TRNS was selected as the external supporting navigation system. Similarly, in the next intervals CVNS and GNSS were successively selected. According to the results of simulation and experiments, the novel developed measurement system is characterized by high accuracy, self-adaption and fault tolerance.

In the novel developed measurement system, we set INS as the basic navigation system, because it has the advantages of strong autonomy, instantaneous navigation parameters and good concealment, which lead to the all-weather global operation of the system. During functioning of the novel developed measurement system, we always select only one external supporting sensor to combine with the INS in each time interval, which can guarantee strong anti-interference capability (*e.g.* anti-electromagnetic interference in battlefield environments) of the whole measurement system.

6. Conclusions

The paper presents a method of developing a variable structure measurement system with intelligent components. In order to achieve this goal, a numerical criterion of the degree of observability and algorithms for constructing prediction algorithms (*e.g.* modified self-organization algorithms) are proposed. On the basis of the Peter K. Anokhin's functional system theory, a novel measurement system with a variable structure is developed for improving accuracy of the system and adapting it to changes of environment. The new proposed measurement system has an intelligent decision-making capability and guarantees continuous optimization of the system structure. According to the results of simulation with the use of practical data as well as the results of field tests, the novel developed measurement system is characterized by high accuracy, self-adaption, strong anti-interference capability and fault tolerance.

Acknowledgement

This research was supported by the Programme of Introducing Talents of Discipline to Universities in P.R. China ("111 program" No. B 16025) and the Russian Foundation for Basic Research (Project No. 16-8-00522).

References

[1] Selezneva, M.S., Neusypin, K.A. (2016). Development of a measurement complex with intelligent component. *Measurement Techniques*, 59(9), 916–922.

[2] Anokhin, P.K. (1974). *Biology and neurophysiology of the conditioned reflex and its role in adaptive behavior*. Pergamon Press, 190–254.

[3] Proletarsky, A.V., Shen, K., Neusypin, K.A. (2015). Intelligent control systems: Contemporary problems in theory and implementation in practice. *2015 5th International Workshop on Computer Science and Engineering: Information Processing and Control Engineering*, Apr. 15–17, Moscow, 39–47.

[4] Groves, P.D. (2013). *Principles of GNSS, inertial, and multisensor integrated navigation systems*. Artech House, Inc., Boston, MA, USA, 419–448.

[5] Mirosław, Ś., Magdalena, D. (2015). Application of Kalman filter in navigation process of automated guided vehicles. *Metrol. Meas. Syst.*, 22(3), 443–454.

[6] Neusypin, K.A., Proletarsky, A.V., Shen, K., *et al*. (2014). Aircraft self-organization algorithm with redundant trend. *Journal of Nanjing University of Science and Technology*, 5, 602–607.

[7] Shen, K., Neusypin, K.A., Proletarsky, A.V. (2014). On state estimation of dynamic systems by applying scalar estimation algorithms. *Proceedings of 2014 IEEE Chinese Guidance, Navigation and Control Conference*, Aug. 8–10, Yantai, China, 124–129.

[8] Chen, Z. (1991). Local observability and its application to multiple measurement estimation. *IEEE Transactions on Industrial Electronics*, 38(6), 491–496.

[9] Proletarsky, A.V., Nikiforov, V.M., Neusypin, K.A. (2014). Certain aspects of designing the control complex of an advanced spacecraft. *Systemy I Pribory Upravleniia*, 1, 5–11.

[10] Shen, K., Proletarsky, A.V., Neusypin, K.A. (2016). Algorithms of constructing models for compensating navigation systems of unmanned aerial vehicles. *2016 International Conference on Robotics and Automation Engineering*, Aug. 27–29, Jeju-Do, South Korea, 104–108.

[11] Groves, P.D., Handley, R.J., Runnalls, A.R. (2006). Optimising the integration of terrain-referenced navigation with INS and GPS. *Journal of Navigation*, 59 (1), 71–89.

[12] Won, D.H., Lee, E., Heo, M., Sung, S. Lee, J., Lee, Y.J. (2014). GNSS integration with vision-based navigation for low GNSS visibility conditions. *GPS Solutions*, 18(2), 177–187.

[13] Carlson, N.A. (1990). Federated square root filter for decentralized parallel processors. *IEEE Transactions on Aerospace and Electronic Systems*, 26(3), 517–525.

[14] Xing, Z.R., Xia, Y.Q. (2016). Distributed federated Kalman filter fusion over multi-sensor unreliable networked systems. *IEEE Transactions on Circuits and Systems*, 63(10), 1714–1725.