Nonparametric Method for Aircraft Sensor Fault 
Real-Time Detection and Localization

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Abstract
This paper is a part of a series of articles on unified nonparametric methods in dynamic systems theory. Here the authors propose a new method for dynamic system sensor fault real-time detection and localization based only on some past measurements of monitored system input-output signals. The described nonparametric method needs no any priori information on system or sensor model parameters and does not require functional redundancy, identification, prediction, training or statistical calculations. An example of nonparametric detection and localization of aircraft multiple sensor faults is presented.

Keywords: aircraft, sensor, fault, detection, localization, nonparametric, model-free, real-time, parametric uncertainty

1. Introduction
There are a large number of methods for dynamic system sensor fault detection and localization [1–20]. All of them can be divided into two broad groups: parametric (model-based) [8–14] and nonparametric (model-free, data-driven, data-based, signal-based, history-based, etc.) [15–20].

Parametric (model-based) methods are the best known and are considered classical. They directly or indirectly use the parameters of mathematical models of real systems, the values of which are given a priori or evaluated during identification. Two approaches to sensor fault monitoring by model-based methods in the parameter and signal spaces are known.

In the first case, the current values of some system parameters, which are compared with their nominal values, are estimated using parametric identification methods. The main limitation of this approach in aircraft sensor monitoring is the impossibility of identifying the open-loop model parameters of an aircraft under closed-loop control [21]. To ensure the aircraft model identifiability in such cases, it is necessary to apply active identification algorithms with feeding the high-excited signals directly to the control actuators. This can significantly reduce the aircraft flight safety, especially in the events of sensor fault.

The signal space model-based methods are focused on generating and analyzing some residual between the output signals of a real system and its mathematical model. The most common way to generate such a residual is to restore and predict the system state vector with the subsequent determination of its measurement vector. However, to solve these problems it is also necessary to know the exact and actual values of system model parameters, that can be difficult in practice [22–24]. The inevitable model errors lead to an increase in the monitoring criteria threshold values, which, in turn, leads to an increase in the faults detection time and to a decrease in localization reliability.

Nonparametric (model-free) methods, unlike traditional ones, do not require information about the parameters of monitored system models and are based only on the analysis of measurements of their input and output signals. Such methods consider the monitored system in the form of a “black box” and allow monitoring problem solving under complete parametric uncertainty. The well-known nonparametric methods require either their preliminary training or long-time tuning for a specific system (neural...
network, genetic, fuzzy logic, etc.), or based on statistical (probabilistic) algorithms. All statistical algorithms require a sufficiently large data sample for the estimation of the statistical properties of the analyzed variables, which inevitably leads to an increase in the fault detection and localization time. In flight, the application of such approaches may require a time exceeding the control system critical response time, and the aircraft may go into an unrecoverable state.

This paper extends application area of a series of previously developed unified nonparametric methods in dynamic systems theory on sensor fault detection and localization problems [25–30]. The proposed method is based on the measurements of the aircraft controls and states only. It doesn’t require a priori information of the aircraft model parameters, statistical calculations, long time tuning or training. It has a very simple form and is based on algebraic solvability condition for the aircraft model identification equation. The scope of the paper is limited to deterministic stationary discrete-state linear completely observable models.

2. Nonparametric discrete aircraft sensor fault detection and localization problem

Let the models of aircraft dynamics with non-faulted and faulted sensors are represented in the state space as

\[ x_{i+1} = Ax_{i} + Bu_{i}, \quad y_{i} = Cx_{i}, \quad (1) \]

\[ x_{i+1} = Ax_{i} + Bu_{i}, \quad y_{i} = FCx_{i}, \quad (2) \]

where \( A, B, C \) — the eigen-dynamics, control efficiency and measurement matrices; \( x, u, y \) — the state, control and measurement vectors of length \( n_{x}, n_{u}, n_{y} \); \( i = 0,1,...,l-1; j = l,l+1,... \) — the discrete times before and after the occurrence of sensor fault; \( l \) — the instant a fault occurs; \( F = \text{diag}[f(1) \ldots f(k) \ldots f(n_{y})] \) — the sensor fault (calibration error) matrix, \( f(\ast) \neq 1 \) for a non-faulted sensors, \( 0 < f(\ast) < 1 \) for faulted sensors.

It is necessary, without any priori information on the aircraft model parameters \( A, B, C, \) based on the controls \( u \) and measurements \( y \) only, to detect the time of fault and to localize the faulted aircraft sensors.

Suppose that we have some series of the measurements. Then the aircraft models (1), (2) can be written in matrix forms

\[ X_{i+1} = AX_{i} + BU_{i}, \quad Y_{i} = CX_{i}, \quad (3) \]

\[ X_{i+1} = AX_{i} + BU_{i}, \quad Y_{i} = FCX_{i}, \quad (4) \]

where \( h, h' \) — the numbers of measurements in non-faulted and faulted cases, \( X_{i} = [x_{i}, x_{i+2} \ldots x_{i+h}]^{T}, \]

\[ X_{i} = [x_{i}, x_{i+1} \ldots x_{i+h'}]. U_{i} = [u_{i}, u_{i+1} \ldots u_{i+h'}]. Y_{i} = [y_{i}, y_{i+1} \ldots y_{i+h'}]. \]

For completely observable model \( (C^{-1}CaI) \) the state matrices can be recovered by the expressions

\[ X_{i} = C^{-1}Y_{i}, \quad (5) \]

\[ X_{i} = C^{-1}F^{-1}Y_{i}. \quad (6) \]

Then, substituting (5), (6) to (3), (4) gives us the equivalent measurement-space models

\[ Y_{n,i} = CAC^{-1}Y_{i} + CBU_{i}, \]

\[ Y_{n,i} = FCA^{-1}F^{-1}Y_{i} + FCBU_{i}, \]

which can be represented in the form of the matrix equations

\[ [CAC^{-1} CB] [Y_{i}] = Y_{n,i}, \quad (7) \]

\[ [FCA^{-1}F^{-1} FCB] [Y_{i}] = Y_{n,i}. \quad (8) \]

It is known, that any linear matrix equation of the form \( ZQ = W \) with known matrices \( Q, W \) is solvable if and only if the necessary and sufficient solvability condition is satisfied [25]

\[ WQ_{r} = 0, \quad (9) \]

where \( Q_{r} \) — the right-hand full rank zero divisor, such that \( QQ_{r} = 0. \)

According to (9) the equations (7), (8) are solvable if and only if the following conditions are satisfied

\[ Y_{n,i} [Y_{n,i}] = 0, \quad Y_{n,i} [Y_{n,i}] = 0, \quad (10) \]

where

\[ [Y_{1}, \ldots Y_{n}] [Y_{1}, \ldots Y_{n}] = 0, \quad [Y_{1}, \ldots Y_{n}] [Y_{1}, \ldots Y_{n}] = 0. \quad (11) \]

But when the sample window includes both non-faulted and faulted measurements there is no any linear model corresponding with measured signals

\[ Y_{n,i} \neq [Y_{1}, \ldots Y_{n}] + \tilde{R} [U_{i}, \ldots U_{i}], \]

and the solvability condition does not hold

\[ Y_{n,i} [Y_{n,i}] = \tilde{R} [Y_{1}, \ldots Y_{n}] = 0. \quad (12) \]

Having viewed (12) line by line, it can be seen that for the non-faulted measurement channels the solvability conditions are still satisfied, because they are generated by original non-faulted linear model. This allows us to use the row norms of (12) for the \( k \) of \( n_{x} \) measurement channels

\[ Y_{n,i} = [y_{i}^{(1)} \ldots y_{i}^{(k)} \ldots y_{i}^{(n_{x})}]^{T} \]

\[ \sigma_{(k)} = \left\| y_{i}^{(1)} \ldots y_{i}^{(k)} \right\| [U_{i}, U_{i}]^{T} \neq 0 \quad (13) \]

as nonparametric criteria for aircraft sensor fault detection and localization.
3. Nonparametric aircraft sensor fault detection and localization example

To verify the proposed method a midrange passenger aircraft dynamics was simulated by the discrete state-space model (1), where [25]:

\[
A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}, \quad B = \begin{bmatrix} B_{11} \\ B_{12} \end{bmatrix}, \quad C = I ,
\]

\[
A_1 = \begin{bmatrix} 0.9998 & -0.1021 & -0.9981 & 0.0000 \\ -0.0001 & 0.9907 & 0.0000 & 0.0100 \\ 0.0001 & 0.0093 & 0.9999 & 0.0000 \\ 0.0000 & -0.0079 & 0.0000 & 0.9973 \end{bmatrix}, \quad B_{11} = \begin{bmatrix} 1.0003 \\ -0.0344 \\ -0.0199 \\ 0.0000 \end{bmatrix}, \quad B_{12} = \begin{bmatrix} 0.0111 \\ 0.9650 \\ 0.020 \\ 0.1000 \end{bmatrix},
\]

\[
A_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0.00018 & 0.00008 & 0 & 0 \\ 0 & 0 & 0 & -0.00338 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad B_{21} = \begin{bmatrix} 0 \\ -0.00338 \\ 0.00009 \\ 0.00009 \end{bmatrix}, \quad B_{22} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}
\]

\[
x = [\Delta V \Delta \alpha \Delta \beta \Delta \omega_\alpha \Delta \omega_\beta \Delta \gamma]T \quad \text{— the state vector of flying speed (km/h), angles of attack, pitch, slip, and roll (deg);}
\]

\[
u = [u_{a,i} \ u_{a,j} \ u_{a} \ u_{n} \ u_{\alpha,i} \ u_{\alpha,j} \ u_{\beta}]T \quad \text{— the control vector of right and left elevators, stabilizer, rudder, right and left ailerons, right and left interceptors deflection angles (deg)}.
\]

Fig. 1 shows the modelled aircraft controls of the form \( \sin(wt) \) with periodic deflection of the rudder \( (w=0.1 \text{ rad/sec}) \), in-phase deflection of elevators \( (w=0.05 \text{ rad/sec}) \) and differential deflection of ailerons \( (w=0.007 \text{ rad/sec}) \). The stabilizer and interceptors were set in zero positions.

The single faults \( f(*)=0.9999 \) were sequentially injected every 5 seconds in every sensor and the multiply fault with the same calibration errors in all rotational speed sensors was injected at 45 second.

Fig. 2 shows the state measurements for non-faulted and faulted cases. As one can see, such kind of faults are visually undetectable at this scale because the graphs in non-faulted and faulted cases are fully coincide.

Fig. 3, 4 show the values of detecting and localizing criteria (13) for sample width \( h=17 \) in different time scales. As one can see, they are close to zero within the accuracy to computational errors when the aircraft model parameters remain constant. All sensor faults result in the clearly visible pulses with amplitudes of 4–6 orders and widths equal to \( h+1 \). These results confirm the high sensitivity of proposed method concerning sensor calibration error in fourth decimal place only.

From fig. 4 it is obvious that the algorithm can detect and localize sensor fault immediately after the first faulted measurement becomes available and has a very short tune time. For this example with sample rate \( \Delta t = 0.01 \text{ seconds} \) and the nonparametric algorithm has tune time \( t_{\text{tun}} = \Delta t(h+1) = 0.18 \text{ seconds} \) only. This is due to the fact that in the current situation for the existence of the right-hand zero divisors (11) it is sufficient to accumulate \( n_{s}+n_{s}+1=17 \) columns of past states and controls to detect their linear dependences.

4. Conclusion

As a result the new nonparametric method for aircraft sensor fault real-time detection and localization, based only on control and state measurements, is developed.

The main advantage of the method is its independence from the aircraft model parameters, that completely eliminates modelling errors and guarantees its efficiency in a full parametric uncertainty even in the case of aircraft model unidentifiability. It does not require sensor functional redundancy, test control signals, or state observing, model identification and aircraft dynamic prediction problems solution.

Unlike wide known nonparametric methods it has a very simple form and need no a priori training, long time tuning or statistical calculations. This makes it possible to significantly increase the reliability and speed of aircraft sensor fault real-time detection and localization problem solution.

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Figure 1. Aircraft controls.

Figure 2. Aircraft state measurements.
Figure 3. Sensor fault detection and localization criteria.

Figure 4. Sensor fault detection and localization scaled-up criteria.
References

[1] Zolghadri A, Henry D, Cieslak J, Efimov D and Goupil P 2013 Fault diagnosis and fault-tolerant control and guidance for aerospace vehicles: from theory to application (London: Springer)

[2] Hajiyev C and Caliskan F 2013 Fault diagnosis and reconfiguration in flight control systems (NY: Springer)

[3] Qi X, Theilliel D, Qi J, Zhang Y, Han J, Song D, Wang L and Xia Y 2013 Conference on Control and Fault-Tolerant Systems (SysTol) pp 132–9

[4] Hou Z S and Wang Z 2013 Information Sciences 235 3–35

[5] Samy I, Postlethwaite I and Gu D W 2011 Control Engineering Practice 7 658–74

[6] Heredia G, Ollero A Bejar M and Mahtani R 2008 Mechatronics 2 90–9

[7] Boníe M, Castaldi P, Geri W and Simani S 2006 International journal of adaptive control and signal processing 8 381–408

[8] Ding S 2012 Model-based fault diagnosis techniques: design schemes, algorithms and tools (London: Springer)

[9] Fravolini M L, Napolitano M R, Del Core G and Papa U 2018 Control Engineering Practice 78 196–212

[10] De Loza A F, Cieslak J, Henry D, Dávila J and Zolghadri A 2015 JET Control Theory & Applications 4 598–607

[11] Ansari A and Bernstein D S 2016 American Control Conference (ACC) 5951–6

[12] Lu P, Van Eyken L, Van Kampen E J and Chu Q P 2015 AIAA Guidance, Navigation, and Control Conference 1311

[13] Freeman P, Seiler P and Balas G J 2013 Control Engineering Practice 10 1290–301

[14] Eubank R D, Atkins E M and Ogura S 2010 AIAA Guidance, Navigation and Control Conference 1–14

[15] Linares R, Vittaldev V and Godinez H C 2018 Handbook of Dynamic Data Driven Applications Systems (Cham: Springer)

[16] El-Kouyuk M, Bennammar M, Meskin N, Al-Naemi M and Langari R 2014 Information Sciences 259 346–58

[17] Fravolini M L, Del Core G, Papa U, Valigi P and Napolitano M R 2019 IEEE Transactions on Control Systems Technology 1 234–48

[18] Hou Z and Jin S 2013 Model free adaptive control: theory and applications (NW: CRC press)

[19] Sarkar S, Jin X and Ray A 2011 Journal of Engineering for Gas Turbines and Power 8 081602

[20] Wang K, Chen J and Song Z 2017 Journal of Process Control 54 152–71

[21] Zybín E Yu 2015 Izvestiya SFedU. Engineering Sciences 6 160–70

[22] Korsun O N, Stulovskii A V, Balyk O A and Zolotava M V 2018 IOP Conference Series: Materials Science and Engineering 312 012015

[23] Korsun O N, Stulovskii A V, Orvshenko V N and Kanyshev A V 2018 Journal of Computer and Systems Sciences International 3 374–89

[24] Korsun O N, Om M H, Latt K Z and Stulovskii A V 2017 Procedia Computer Science 67–74

[25] Chekin A Yu, Bondarenko Yu V, Zybín E Yu and Kiselev M A 2019 IOP Conference Series: Materials Science and Engineering 476 012003

[26] Glasov V V, Zybín E Yu and Kosyanchuk V V 2019 IOP Conference Series: Materials Science and Engineering 476 012011

[27] Karpenko S S, Zybín E Yu and Kosyanchuk V V 2018 IOP Conference Series: Materials Science and Engineering 312 012010

[28] Terent’yev M N, Karpenko S S, Zybín E Yu and Kosyanchuk V V 2018 IOP Conference Series: Materials Science and Engineering 312 012025

[29] Zybín, Kosyanchuk V and Karpenko S 2017 MATEC Web of Conferences 99 03011

[30] Zybín E Y and Kosyanchuk V V 2016 Journal of Computer and Systems Sciences International 4 546–57