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Faults Self-detection of Self-validating Flush Air Data Sensing System

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Abstract

The flush air data sensing technology, which is one of the most advanced flight parameters measuring strategies in the world, can be employed in the flight environments with high speed, large angle of attack, and fine aircraft stealth design. As the source of acquiring flight parameters, its measurement value quality will affect the control precision of aircrafts directly, and even threaten the safety. To enhance the reliability of flight parameters, a novel prototype of self-validating air data systems (SVADS) is proposed, in which the merits of flush air data system and self-validating sensors technologies are fully combined. The SVADS not only can output the traditional flight parameters such as angle of attack, angle of sideslip, altitude and Mach number, but also can perform the fault self-detection, self-diagnosis and status self-estimation. The failure can be substituted by an optimal estimated value by means of fault recovery, and the working status identifier and dynamic uncertainty of above flight parameters are also described. A real experimental platform of SVADS was designed to acquire the output signals, and a part of self-validating functions based on wavelet kernel principle component analysis (WKPCA) has been implemented. Multiple faults can be detected by using redundancy information fully.

Keywords*: Air data systems; status self-validation; faults self-detection; wavelet kernel principle component analysis*

1. Introduction

Recently National Aeronautics and Space Administration (NASA) has developed the flush air data sensing (FADS) system, which has replaced the traditional Pitot tube with distributed-mounted pressure points, in order to meet the needs of aircraft stealth capabilities, redundancy design, and high Mach number flight [1-2]. However, in real-world flight, the FADS system cannot acquire its own working status which will directly decide whether the current raw measurements value (RWV) can apply to flying control system, *i.e.*, the fault self-detection and self-diagnosis function is absent [3]. In addition, when faults occur, the RWV has deviated from the expected measurements. To ensure the temporary safety of aircrafts, humans hope that the faulty measurements can be substituted by best estimated value on line, which can scramble the valuable time to take emergency actions *i.e.*, data recovery function under faults is also in shortage. Further, the measurements accuracy will be decline after numerous flights. If the accuracy or on-line uncertainty information is absent, the flying control and decision will be affected. Based on the uncertainty and faults diagnosis results, the system working information should be given, however, the status self-estimation function lacks.

Aiming at the above shortcomings, a novel prototype of self-validating air data sensing (SVADS) systems is proposed to validate the output of the air data system and further to provide the reliability of the measurement value. Combined some previous work[4-7], the

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functional architecture of traditional air data system and the proposed SVADS is proposed as shown in Figure 1 a) and b).

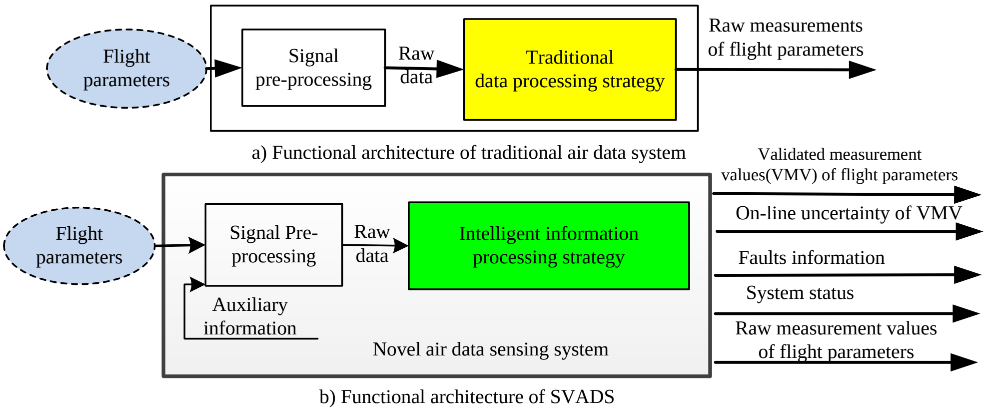

Figure 1. Comparison of Functional Architecture between SVADS System and Traditional Ones

To sum up, the proposed SVADS system not only can output RMV of flight parameters such as angle of attack, angle of sideslip, altitude and Mach number, but also can perform the fault self-detection, self-diagnosis, self-recovery under faults situation, and status self-estimation on line. The faulty RMV can be substituted by an optimal estimated value which is called validated measurement value (VMV) by using fault recovery method, and the working status identifier and dynamic uncertainty of above flight parameters are also described to indicate the measurement value accuracy and reliability. Due to the limited length of paper, the fault self-detection strategy, which is one of three self-validating techniques in SVADS system, is emphasized here.

There have been a lot of efforts devoted to performing fault self-detection of air data system in recent years. These algorithms are mostly on statistic model; signal analyzes technology, neural networks and so on. For example, the statistic model based adaptive estimation method has been proposed for the failure detection of air data sensors [8], the principle component analysis method has been put up for monitoring electrical consumption status of academic buildings [9], the neural networks (NN) based faults detection algorithm is studied for monitoring on-line temperature sensor[10]. However, the above methods have their own shortcomings in FDI field. Firstly, the statistic theory based fault detection model needs a large number of samples under different working situation, which refers to the combination of different angle of attack, angle of sideslip, altitude and Mach number in this paper. Secondly, the PCA can process linear data sample, but it has its own weak point on extracting the real-world non-linear faults features. Thirdly, the NN model can process the non-linear feature sample, but it needs a lager mount of samples and meanwhile the model is so complex that it would affect the real-time performance of SVADS system.

Aim at the above shortcomings, a better status self-validation model should be established for faults detection, in which it can have good fault detection accuracy under small sample problems, simple structure for model reconstruction, and favorable real-time capacity. Therefore, the wavelet kernel principle component analysis (WKPCA) algorithm is proposed for rapid faults detection of SVADS system. The wavelet kernel has high-resolution ability, which can detect the instantaneous failure such as impact and interference. The KPCA can map the non-linear faults feature in the low-dimension space into linear high-dimension one, which ensures the non-linear faults features processing performance in SVADS system. Their merits are combined in our proposed strategy for primary status self-validation of air data system.

2. Overview of SVADS System

2.1. Structure Composition of SVADS System

The SVADS system inherits the merits of both flush air data sensing (FADS) system and self-validating technology, which plays an important role in improving reliability of flight parameters measurement values itself and enhancing the safety in aerospace industry. Detailed description of the functional construction models is shown in Figure 2, which is composed of flush pressure ports mounted into top parts of aircrafts, windpipes, array of pressure sensors, signal pretreatment, input interface involving known auxiliary aerodynamics model and other historical information, and processor with implementing self-validating algorithms, and output interface. Main self-validation functions and the implementation flowchart will be explained as follows.

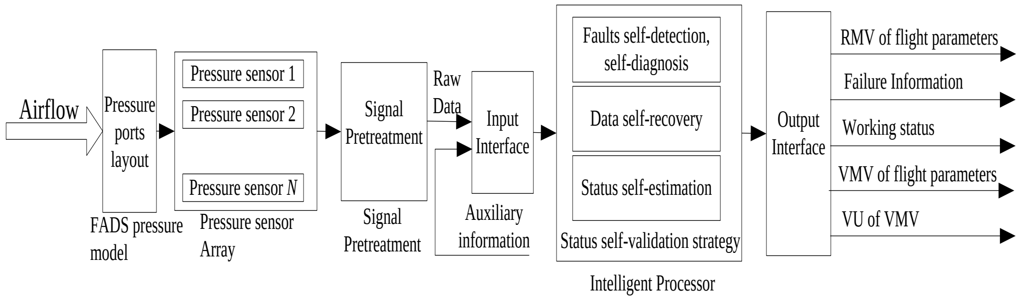

Figure 2. Construction Models of SVADS System

2.2. Failure Self-Detection and Self-Diagnosis

Once one or more pressure measurements are faulty, the corresponding flight parameter is invalid. At this time, it should give failure alarm; therefore, the key issue is how to judge measurement value unreliability with prompt solution.

Failure detection, isolation and further diagnosis are a key part of SVADS system. If faults come, the incorrect measurements should be detected, identified and isolated to avoid its continuous propagation. A serious flight disaster can be occurred when the wrong air data are used in the flying control system. By using the failure self-detection and self-diagnosis, the SVADS system can output the working status and the detailed failure information such as what type of, when, and where faults occur. This will benefit the further device maintenance, and can also be ready for latter data recovery under faults.

2.3. Data Self-Recovery under Faults

Data self-recovery under faults is a particular trait of the proposed SVADS system. When faults exist, the failure sources can be detected and identified, however, it is not enough for aircrafts. To maintain the reasonable control rule, the well-evaluated values of true flight parameters such as angle of attack, angle of sideslip, pressure-altitude and Mach number are essential to the flying control system, which can ensure the safety of aircrafts in the short time. In the SVADS system, the data recovery results are also called as validated measurement value (VMS), and they can be acquired by using the redundancy pressure ports knowledge. The data validation results are still expressed by electric signals of pressure sensors.

2.4. Status Self-Estimation Model

Status self-estimation of SVADS system is mainly to estimate the on-line validated uncertainty (VU) of validated flight parameters measurements. And the uncertainty evaluation is used to reflect the accuracy of measurement value. Being different from the traditional static uncertainty evaluating method, the self-validating sensor is built on the dynamic process, in which each measurement should have its corresponding uncertainty estimation result. In the status self-estimation process, the difficulty lies in the real-time, dynamic estimation and small sample, in which the faults information can be fully employed. No matter which faults, the best evaluated values of data recovery model can temporarily be served as the validated outputs. Its reliability under failures will become lower with the elapse of time, and the uncertainty will becomes higher correspondingly. Generally, the instantaneous faults last for only a short period, and the VU is small; however, the permanent faults always exist, and its value is larger to reflect the long-term negative effect.

2.5. Implementation of Self-Validation Functions

The proposed SVADS system centers on the reliability, and aims at resolving some key issues, how to evaluate its working status, how to improve its reliability level of measurements once it is faulty, and how to indicate its reliability level. The data validation process of flight parameters can be illustrated as shown in Figure 3.

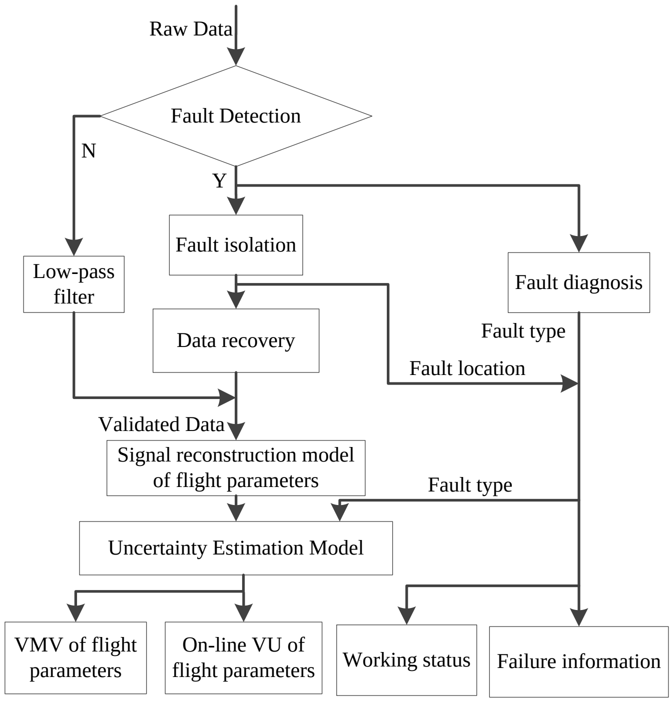

Figure 3. Flowchart of Status Self-Validation Implementation

From Figure 3, the raw data of all pressure sensors whose number is set by the pressure ports are first input into the faults detection model. When faults are detection, faults isolation model can further identify the number of failure and corresponding location of fault sources, and meanwhile the fault diagnosis model could diagnose the faults type such as the instantaneous impact or disturbance fault, constant bias faults or no output. After faults are identified and isolated, the wrong sensor output will be picked out, and it is replaced and validated by a best estimated value by using data recovery model. These validated sensor outputs can be used to participate the following flight parameters reconstruction. When faults are not detected, the raw data will be processed simply by the low-pass filter, and the filtered sensors measurements are also employed to obtain the physical flight parameters. The outputs of signal construction model are exactly the validated flight parameters measurements. Based on the established signal reconstruction model and faults information, the uncertainty propagation law can be derived, and the corresponding the uncertainty estimation model can be built. The outputs of the uncertainty estimation model are the VU of flights parameters.

3. Faults Self-Detection Methodology of SVADS System

3.1. Faults Detection Overview of SVADS System

The functional diagram of faults self-detection strategy is shown in Figure 4, in which the WKPCA algorithm is employed to detect the non-linear faults. The process mainly concludes off-line WKPCA based model establishment and on-line detection. The proposed WKPCA can efficiently compute principle components in high-dimensional feature spaces by means of integral operators and nonlinear kernel functions. It is the participation of kernels that can handle a wide range of nonlinearities, especially the wavelet kernel. Compared to other nonlinear methods, the main advantage of WKPCA is that it does not involve nonlinear optimization; it essentially requires only linear algebra, making it as simple as standard PCA. In addition, WKPCA does not require that the number of components to be extracted be specified prior to modeling. Due to these merits, WKPCA has shown better performance than linear PCA in feature extraction and classification in nonlinear systems. To capture the inner relationship in feature space and extend to the process monitoring, the monitoring chart of the squared prediction error (SPE) is generated. When the pressure measurements from all the pressure ports are confirmed to be fault free, the SPE value will be smaller than the setting threshold SPE_{limit} which is computed off-line by using the normal data sample. However, once some faults are detected, the correlation among pressure values in the feature space is broken, the corresponding SPE will be larger than the SPE_{limit}. Detailed WKPCA algorithm and the realization process will be discussed in Section B and C respectively.

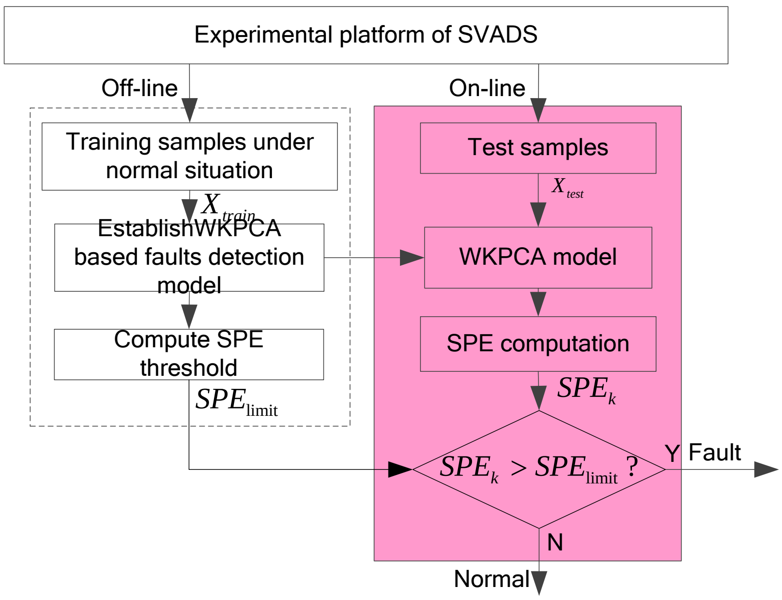

Figure 4. Functional Block Diagram of WKPCA based Fault Detection

3.2. Faults Detection Strategy by Sing WKPCA Model

Detailed explanation and introduction of KPCA theory can refer to [11], and its application to failure self-validation is emphasized in this paper. The faults detection procedures are follows:

Firstly, construct the training samples $\boldsymbol{X}_{train} \in \boldsymbol{R}^{m\times n}$ wherein the *m* represents the number of samples, and n is equal to the number of pressure ports. The sample distribution is shown in Table I wherein P_i^m is the pressure measurement value at ith pressure port (i=11 in this paper).

Table 1. Distribution of Training Samples

No.	Sample vector	Vector construction
1	$\mathbf{X_1}$	$[P_1^1\ P_2^1\ \dots\ P_{11}^1]$
2	$\mathbf{X_2}$	$[P_1^2\ P_2^2\ \dots\ P_{11}^2]$
…	…	…
m	$\mathbf{X_m}$	$[P_1^m\ P_2^m\ \dots P_{11}^m]$

Secondly, build the WKPCA based faults detection model off-line. To remove the amplitude influence of sample data, the normalization is necessary. The normalized sample is then mapped into high-dimension linear feature space by using the Morlet wavelet kernel. After performing the mean centering in the high-dimensional space, the principle component space and residual space vectors can be obtained, and the further SPE can be established.

Thirdly, compute the SPE threshold. Based on the scores of training sample in feature space, the threshold SPE_{limit} can be obtained. So far, the WKPCA based faults self-detection of SVADS system model is built off-line.

Fourthly, input the test sample $\boldsymbol{X}_{test} \in \boldsymbol{R}^{k\times n}$ wherein the *k* represents the series of samples, and its distribution is the same as the Table I, i.e., $\boldsymbol{X}_{test}=[P_1^k\ P_2^k\ \dots\ P_{11}^k]$. After the test sample is input into WKPCA model, compute the monitor SPE_k of *k*th test sample in feature space.

Lastly, compare the monitoring value SPE. If SPE_k is larger than the prescriptive value SPE_{limit}, it means that there are erroneous pressure measurements among current eleven pressure ports. In the process of establishing the WKPCA model, the training samples includes the different flight status, therefore, the dynamic changes of flight state cannot be distinguished as faults.

4. Experimental Results and Analysis

To verify the effectiveness of the faults self-detection strategy, the SVADS system experimental platform is designed and common faults coverage analysis is also stated. In this hardware platform, our proposed faults self-detection method will be implemented.

4.1. Experimental Platform Setup

Aiming at the cone-shape nose of the aerodynamic configuration based aircraft; a prototype of SVADS system has been preliminarily designed. The pressure ports layout employs eleven-point cross way, and the material thing of aircraft nose is shown in Figure 5. The prototype design of SVADS system can be described by the electric and airflow connection shown in Figure 6. The designed prototype of SVADS system are consist of airflow pipes that control the flow of air (dynamic pressure) to pressure sensor, eleven high-accuracy pressure sensors which use the vibration cylinder pressure transducer and output temperature-related analog and pressure-related frequency, the signal pickup and information processing unit which will be used to the measure pressure values and accomplish the self-validating algorithm, and 1553B based communication unit which can do data transmission to flying control system.

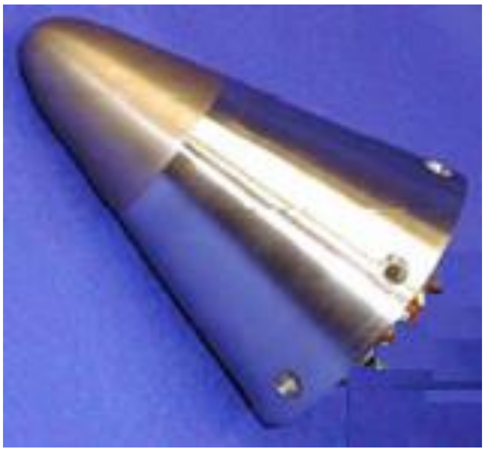

Figure 5. Material Thing Type of Aircraft Nose

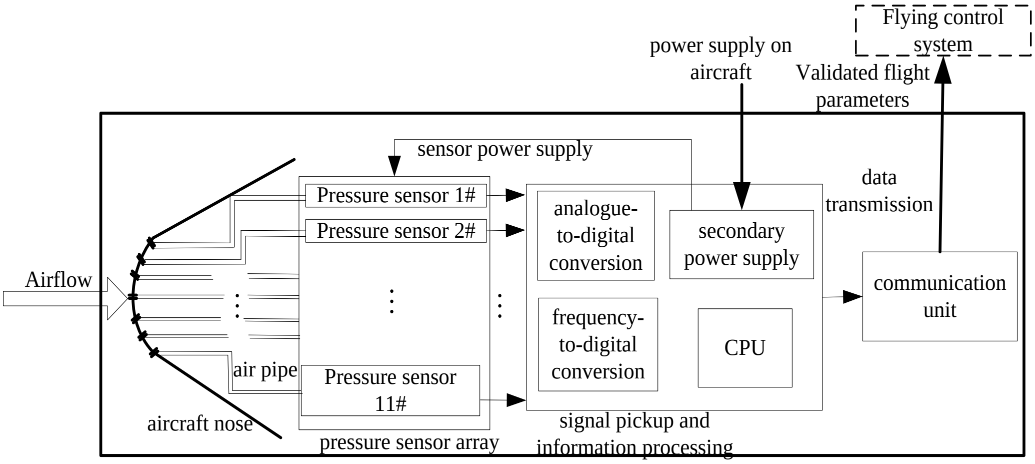

Figure 6. Electric and Airflow Connection Design of SVADS System

The prototype has been tested in the wind tunnel, in which the Mach number is from 0.1 to 1.0, the angle of attack is from -15 degree to +15 degree, the angle of sideslip is also from -15 degree to +15 degree, and the altitude is from 0m to 10000m. Above test is done under normal working situation, and enrich experimental data have been obtained. Based on the prototype of SVADS system, the emulation platform can be built to study the detailed self-validating algorithm. And the platform is based on PC and the functional chart is shown in Figure 7. Once the status self-validation strategy is verified sufficiently on PC, and it would be transplanted to prototype of SVADS system.

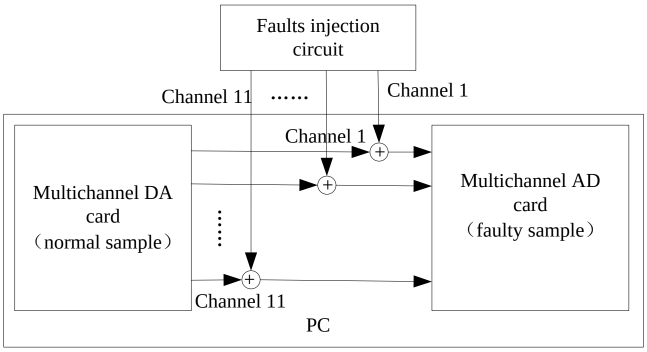

Figure 7. Experimental Platforms for Studying Self-Validating Algorithm

The platform mainly includes the multichannel DA card which produce the normal pressure signal, faults injection circuit which is used to produce the faulty signal and add the faults into the normal one, multichannel AD card which can pick up the final faulty signals, PC which controls the faults injection way. The normal experiment test of prototype can be simulated by using the air data calibrator which can output multichannel gas pressure. Due to the limitation of our laboratory resource, this paper has done 9-channel pressure experiment at different Mach number, different angle of attack, and angle of sideslip.

4.2. Failure Mode Analysis

The research of self-validating algorithm needs faulty sample; however, real fault data is difficult to be captured or it takes some time to accumulate. The normal method is done by faults simulation based on above normal data sample, in which failure mode analysis is necessary.

The faults of airflow pipes often includes: the blockage of pressure ports caused by ice and dust will lead into the no change dynamic pressure when flying condition changes; pipe pressure leak caused by ageing of pipe material and seal ring will lead into sudden change of vertical speed and difficulty building signal reconstruction model; pipe pressure delay caused by the long distance will result in the hysteresis of actual pressure measurements values.

The faults of pressure sensors often includes: no output caused by inner broken wires and power failure will lead into the absence of frequency signals; large fluctuations caused by other residue or pollutants will result in larger fluctuations of frequency values; signal jump caused by lose effectiveness of vibration cylinder will lead into pressure jump; bias fault caused by the absence of temperature compensation will result in bias output.

The faults of signal pickup and information processing unit often includes: analogue-to-digital conversion circuit fault caused by incorrect control command and wrong data bus will output the erroneous temperature information and further pressure measurements accuracy becomes worse; frequency-to-digital conversion circuit fault caused by the disorder of sequencing control will output wrong frequency and further pressure measurements values becomes wrong; CPU reset faults caused by weaker surge characteristic will no output in a short time; secondary power supply fault caused by the loss of power module will always lead into no output.

The faults of 1553B based communication unit faults include BC controller fault and RT terminal failure, which will not transmit the air data information to flying control system.

To sum up, the abnormal pressure outputs types mainly consists of larger fluctuation, jump, bias and constant output as shown in Figure 8.

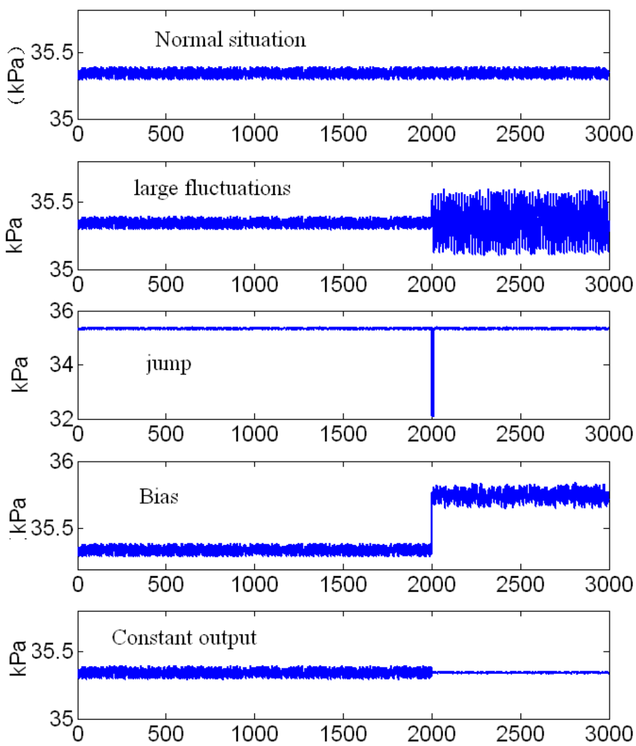

Figure 8. Common Types of Abnormal Pressure Outputs

4.3. Experimental Results under Normal Steady Situation

The experimental process to verify the ability in distinguishing from the normal situation is follows: 1)taken the flight state (altitude 10000m, angle of attack and sideslip 0°, and Mach number 0.8) as an example, the nine-channel pressure can be simulated and outputted by using air data calibrator; 2) the prototype of SVADS system then pick up and acquire the above pressure information, the mean values of all channels are shown in Table II and the RAW of pressure ports are shown in Figure 9; 3) establish the faults detection model by using WKPCA algorithm based on fault free samples, and compute the monitoring threshold SPE; 4) based on the experimental simulation platform in Figure 7, the data shown in Figure 9 can be obtained under normal situation, and then the proposed faults detection strategy can be verified.

Table 2. Mean of Fault-Free Outputs of all Pressure Channels

Chnanel	P1	P2	P3	P4	P5
pressure（kPa)	35.342	38.707	40.309	38.707	35.341
Chnanel	P6	P7	P8	P9	—
pressure（kPa)	35.345	38.709	38.709	35.345	—

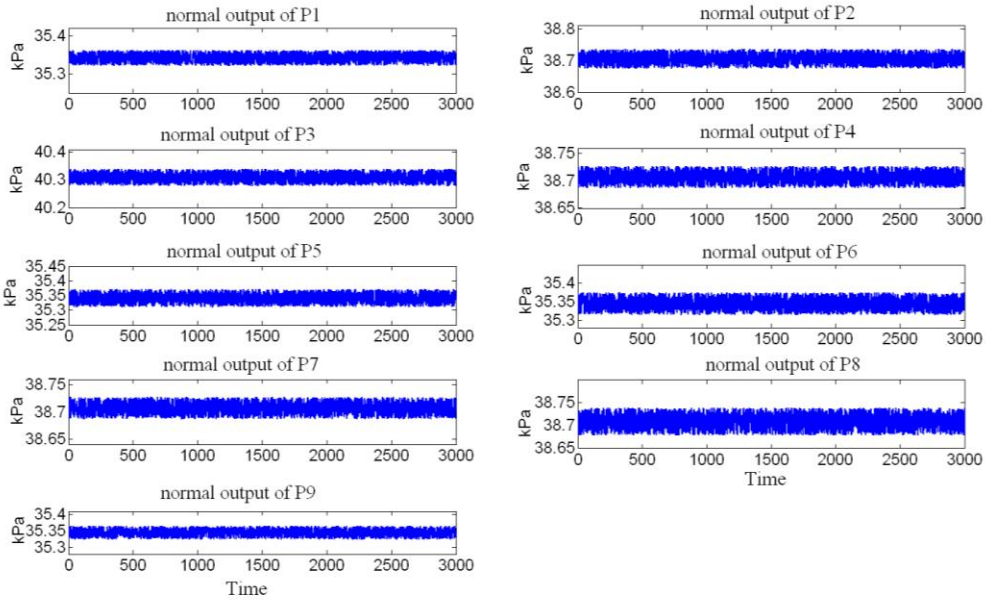

Figure 9. Distributed Pressure Outputs under Steady Flight Status

By using the proposed faults self-detection method, the contribution ratio of principle components is larger than 95%, and the responding number is 6. In residual feature vectors space, the monitor SPE threshold is 4.553 when the confidence level of χ^2-distribution is 99%. The test sample in Figure 9 can be analyzed and the computation results of SPEs are respectively shown in Figure 10.

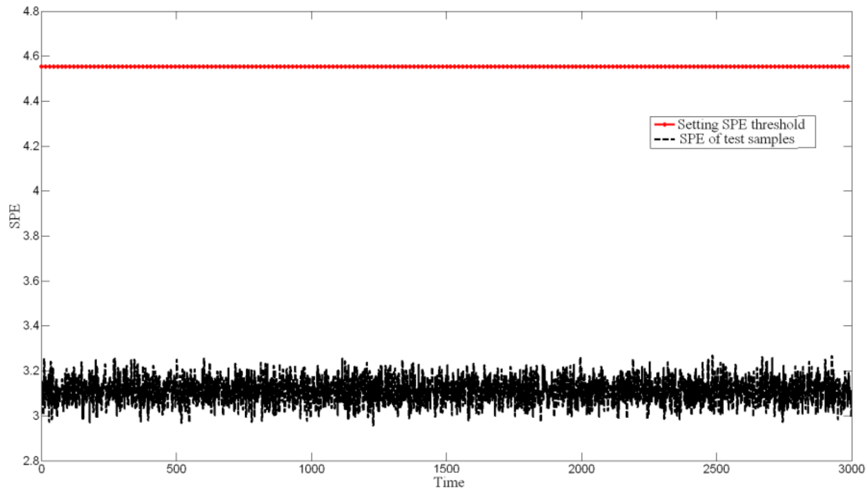

Figure 10. Faults Detection Results under Steady Flight Status

In Figure 10, the obtained SPE of normal test data is about 3.2, which is smaller than the threshold. The inner relationship among nine-channel pressures is not broken, and the distributed pressure signals under normal steady flight status can be distinguished from the faults validly.

4.4. Experimental Results under Normal Flight Status Changes

To distinguish the normal flight status changes from the true faults, the data sample can be obtained by using established experimental simulation platform show in Figure 11. The corresponding status changes are from Mach number 0.5 to 0.7. The computation results of SPE can be further obtained by using the WKPCA model as shown in Figure 12.

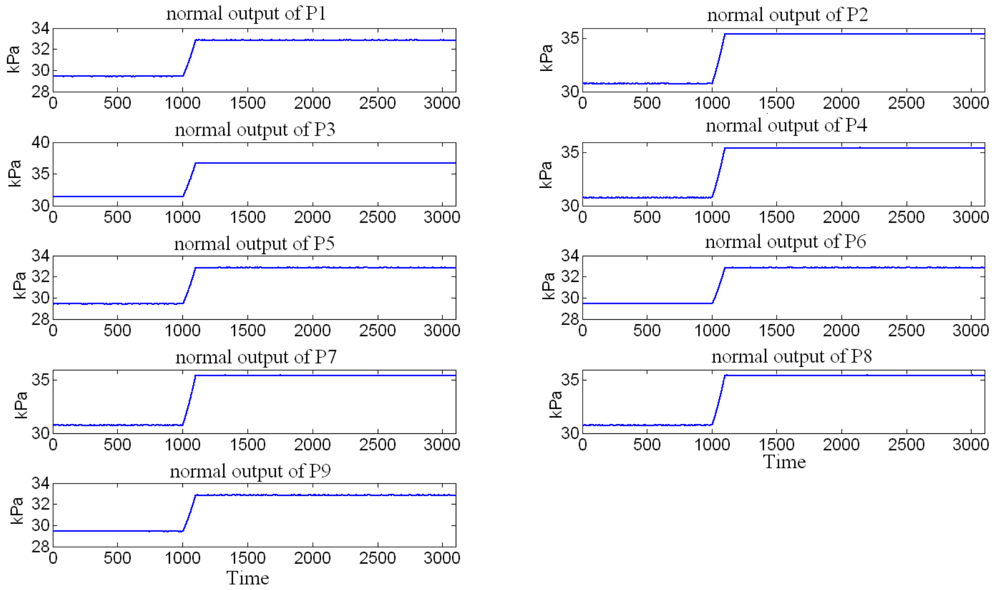

Figure 11. Distributed Pressure Outputs under Flight Status Changes

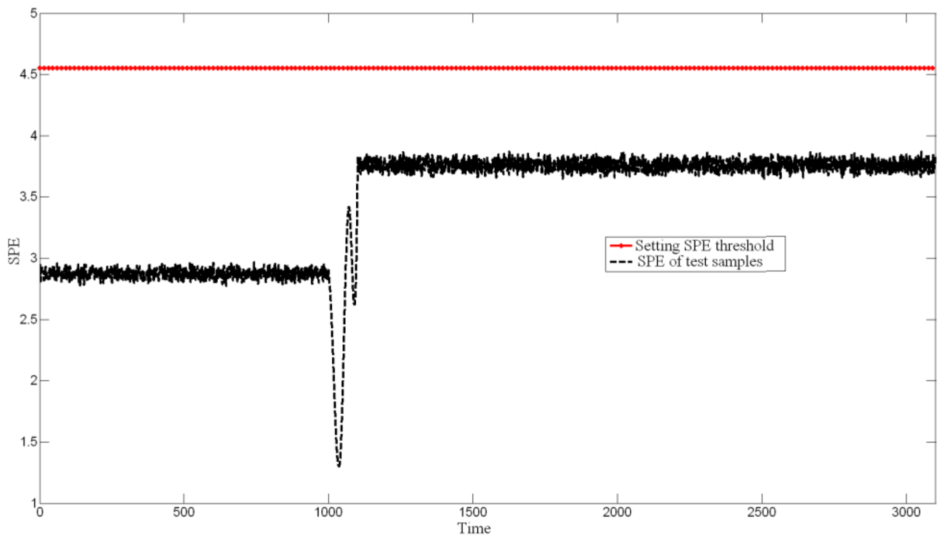

Figure 12. Faults Detection Results under Flight Status Changes

In Figure 12, the SPE in high-dimension survival space are all lower than the setting threshold of SPE by statistic model, which indicates no faults are detected. The changes of SPE values correspond to the moment of flight state changes that Mach number is from 0.5 to 0.7. The above results show that the proposed faults detection strategy can distinguish the ‘fault-like’ changes process of flight status.

4.5. Experimental Results under Faults

To further verify the ability in faults detection of WKPCA model, the fault injection experiments are done. Based on the normal test sample, some typical faults are simulated by using faults addition circuit. The detailed faults are follows: the periodicity disturbance are added to the channel 1 from the 1500th time point to simulate the large pressure fluctuations, the pressure jump faults are added to the channel 4 from the 1000th time point to simulate pressure impact, the larger bias data are added to channel 7 from 1300th time point to simulate the analogue-to-digital conversion circuit fault, and normal pressure is broken from 1500th time point to simulate no output. Because the moments faults occur are different, it contains both the single failure and multiple faults. The above four faults can be output simultaneously to simulate multiple faults situation as shown in Figure 13. The faults detection results of SPE can be further obtained by using the WKPCA model as shown in Figure 14.

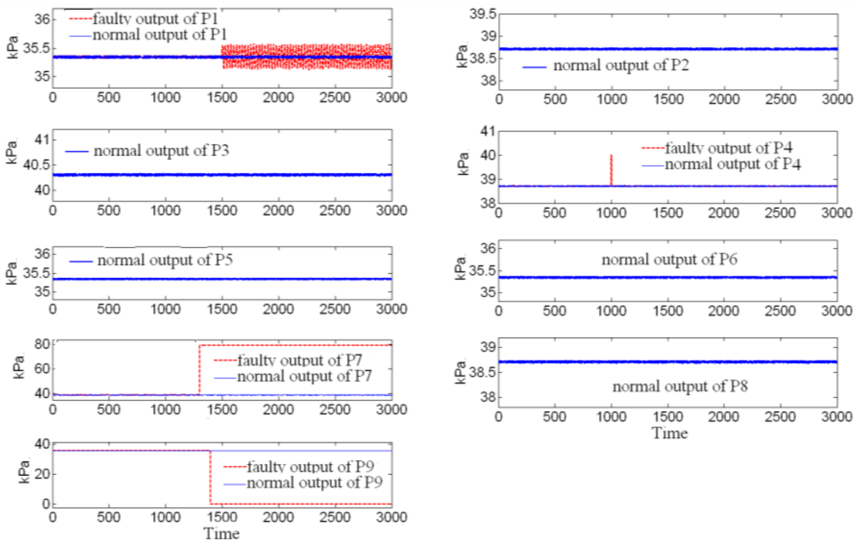

Figure 13. Distributed Pressure Outputs under Faults

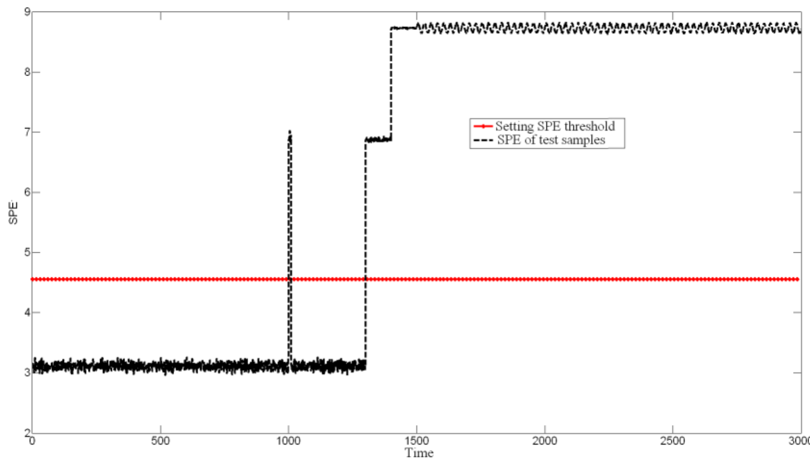

Figure 14. Faults Detection Results under Faults

In Figure 14, the SPE at 1000th time point is clearly higher than threshold of normal SPE, which is consistent with impact fault of pressure port 4, the abnormal SPE between 1300 and 1400th time points are the circuit's faults of pressure port 7, and ones between 1400 and 1500th time points are the failure with no pressure output of port 9. The sudden changes of SPE in Figure 14 also imply the number of abnormal faults at different moments. The two jumps in the high-dimension feature space is consist with the three simulated faults.

5. Conclusion

This paper has proposed a new prototype of air data sensing system, which combines the merits of flush air data system and self-validating sensor technology fully. The SVADS system can improve the measurement value quality of the flight parameters and enhance their reliability, and the novelty lies in that the SVADS not only can output the traditional raw flight parameters, but also can perform the fault self-detection, self-diagnosis, data recovery under faults and status self-estimation. The primary WKPCA based faults self-validation strategy is proposed particularly to implement the part of self-validation functions, in which the high-resolution ability of the wavelet kernel can benefit the instantaneous failure detection and non-linear faults feature in the low-dimension space can be mapped into linear high-dimension one. Based on the detailed faults coverage analysis, a real experimental platform of SVADS was designed to acquire the enrich data sample, and verify the proposed faults detection algorithm. Results show that the proposed WKPCA model can distinguish the normal changes of flight status from the true faults, both single and multiple faults can be detected validly. Our future work is to study the other status self-validation algorithm, in order to further implement the faults self-diagnosis, data recovery under faults and status self-estimation.

Acknowledgments

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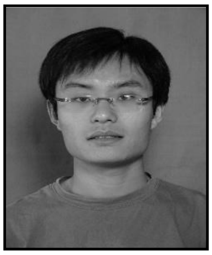

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