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Saadi T. Kurdi[1], Ahmed Hameed Reja[1], Al-Ashmati Akram Fathi Hussein[2]

[1] Electromechanical Engineering Department, University of Technology, Baghdad, Iraq
[2]Alfarahidi University College, Baghdad, Iraq

INCREASE THE AVIATION EFFICIENCY OF UAVs USING ARTIFICIAL NEURAL NETWORKS

Purpose. It is known that the flight of the UAV is conducted by sensors that transmit the performance of the UAV and on the basis of this information is controlled on the UAV and give them the orders which are necessary to perform the task of flying UAV. and normal these faults occur during the flight of unmanned air vehicle (UAV), according to the concepts of aviation is a very critical situation that affects the completion of the mission. These faults are mainly due to failure in the sensors, which can be divided into. Flight Situation is about the flying situation of the aircraft, such as (heading, altitude, airspeed, and vertical speed and angle of attack sensors. And Flight Control Situation, this is about the flight control surfaces such as (rudder, aileron, and elevator deflection), pitch attitude, and roll attitude sensors. This paper presents an effective technique to ensure that the sensors can operate with high efficiency. **Methods**. Two different approaches are used in this work. The first approach is Neural Network (NN) based tool for the modeling, simulation and analysis of aircraft (SFDIA), sensors failure, detection, and identification and accommodation problem. The second approach is Neural Network trained with the (EMRAN) algorithms which is a set of conditions that decide how the (EMRAN) structure should be adapted to better suit the training data. **Results**. The results from the modeling process and analysis of aircraft sensors showed that the neural network based tool (SFDIA) and the (EMRAN) algorithms are able to show high-resolution results in the behavior of sensors and hence in the (UAV) behavior. **Conclusions**. The capabilities of (SFDIA) are a consequence of the extensive modularity of the whole simulation tool. It allows an easy change of unmanned air vehicle (UAV), dynamics and feedback control law as well as Neural Network (NN) estimators and (SFDIA) scheme.

Keywords: Unmanned aircraft vehicle; Sensor fault detection; Fault diagnosis; Aircraft sensors modeling and simulation.

List of Acronyms

UAV - Unmanned Air Vehicle
SFD - Sensor fault detection
SFDIA - Sensor Failure Detection Identification and Accommodation
NN - Artificial Neural Networks
EMRAN - Extended Minimal Resource Allocation Network
RBF - Radial Basis Function

1. Introduction

Unmanned air vehicle (UAV) are complex technical systems. They are out of reach of the pilot. But the name of this aircraft does not fully demonstrate the way in which they are operated. They are in fact not fully self piloted, but also need a pilot sitting at the steering station on the ground, to remotely control it by a wireless manner. The control Process of the (UAV) is through signals transmitted by sensors. In this respect comes the importance of increasing the efficiency of sensors. Which transmit signals back to ground stations [1]. Sensor fault in (UAV) is detected by using two different approaches. The first approach is Radial Basis Function (RBF) NN trained with the Extended Minimal Resource Allocation Network- (EMRAN) algorithms [2, 3]. The second approach, which is presented in this Paper, is based on Knowledge based Neural Network (NN) based tool (SFDIA) Sensor Failure, Detection, Identification and Accommodation problem [4-5]. The tool is based on a (SFDIA) scheme in which learning NNs are used as on-line non-linear approximates of the analytically redundant portion of the system dynamics [6]. This can provide validation capability to measurement devices, allowing sensors failures to be detected, identified and accommodated. Research on fault tolerance based on analytical redundancy has produced a quite mature framework especially for linear systems [7]. But unfortunately, the assumption of linearity is not often valid throughout the whole flight envelope of the aircraft. Thus the performance of a fault tolerance scheme based on such assumption can become inadequate, for example providing a high false alarm rate in a wide portion of the flight envelope. Chow and Willsky (1984) first defined model-based FDI to consist of two main stages; residual generation and residual evaluation [8]. Patton et al. (1989) also outlined the criteria for selecting a suitable FDI approach, two of which were low false alarm rates and fewer missed faults [9]. In this work, SFDIA software has been designed in the Simulink environment. The tool allows evaluating either the open loop or the closed loop performance of the SFDIA scheme that employs different kinds of NN approximators and learning algorithms [10]. The NN structure chosen is based on the Extended-Minimum Resource Allocating Network (EMRAN) Radial Basis Function (RBF), due to its good generalization ability and fast performance [11].The completion of the process has two stages the first stage construction of the scheme NN base (SFDIA),involved the process of modeling and simulation of (Power supply, Engine Condition, Flight Control Situation, Environmental Situation, and the second stage the (EMRAN) algorithms (Extended Minimal Resource Allocation Network) which is a set of conditions that decide how the (EMRAN) structure should be adapted to better suit the training data, using (Mat lab, Simulink program) and Extended-MRAN (EMRAN) algorithms.

2. Neural network-based SFDIA

Analytical redundancy implies that some of the system variables are functionally related namely a variable $y(k)$ can be expressed as function of a suitable set of other variables $Z(k)$ and input commands $U(k)$.

Fig. 1 shows the (SFDIA) scheme.

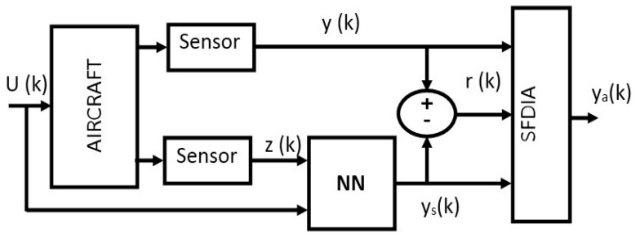


Fig. 1. General SFDIA scheme [12]

$$y_S(k)=f\left[z(k),u(k)\right], \qquad (1)$$

where $u(k)$ – inputs commands. $z(k)$ – function of a suitable set of other variables, $y_S(K)$ - estimation signal provided by estimator (ANN).

The residual signal $r(k)$ is the difference between the sensor output $y(k)$ and its estimation $y_S(k)$ provided by a proper estimator (in this work the estimator is a Neural Networks NN) [13].

$$r(k)=y(k)-y_S(k), \qquad (2)$$

where: $y(k)$ –sensor output, $y_S(k)$ – estimation signal provided by estimator (ANN), $r(k)$ – residual signal.

When the square of this (filtered) residual exceeds predefined threshold, the state of the corresponding sensor is declared suspect and a suitable procedure is called to decide on the health status of this sensor.

Fig. 2 shows a flowchart of the predefined threshold.

If the state of the sensor is then declared faulty, a procedure is enabled, and an accommodated variable $y_a(k)$ are provided as output. In this work the accommodation procedure simply substitutes the faulty measure with the Estimation given by the ANN.

Fig. 3 Shows the accommodation with the estimation given by the ANN.

$$y_a(k)=r(k) \qquad (3)$$

Several options can be added to this basic scheme to increase robustness in presence of noisy measurements and/or intermittent sensor failures [14] Thus, the accommodation procedure substitutes the faulty measurement with the estimation given by the NN [15]. As for any SFDIA approach, the following capabilities are critical:

1) failure detect ability and false alarm rate (the sooner the fault is detected and the least the number of false alarm it is, the better is the SFDI system [16];

2) estimation error (The least is the estimation error; the better is the quality of the accommodation) [17].

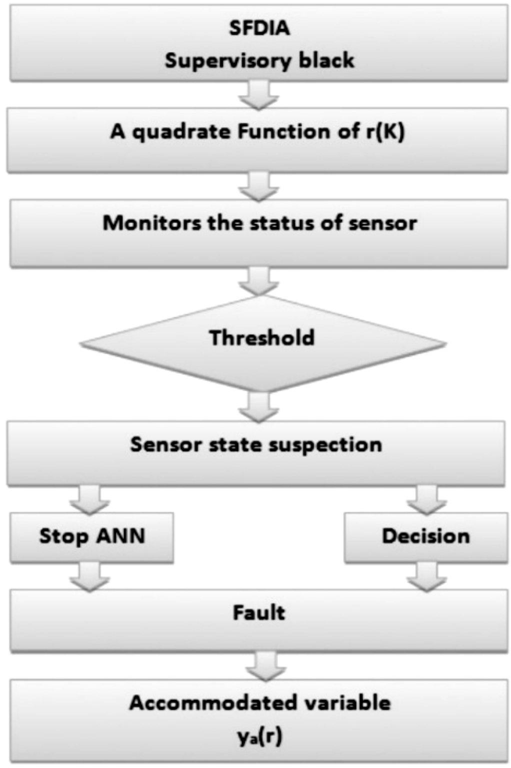


Fig. 2. Predefined Threshold

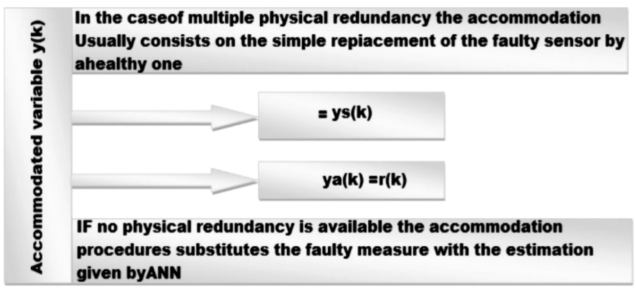


Fig. 3. The accommodation with the estimation given by the ANN

3. The simulation

The Neural Network based SFDIA modeling and simulation toolbox was built under the Math lab and simulink for Technical computing (by The Math works Inc) [18]. In particular the freely available aircraft Sensor Failure, Detection, Identification and Accommodation (SFDIA) toolbox for Mat lab provides powerful tools for aircraft simulation [19-20]. A bank of output estimators has been implemented as showed in Fig. 4.

SFDIA (Sensor Failure Detection Identification and Accommodation).

It is the core of the tool that performs the main SFDIA procedures. It is constituted by two main sub-blocks [21]:

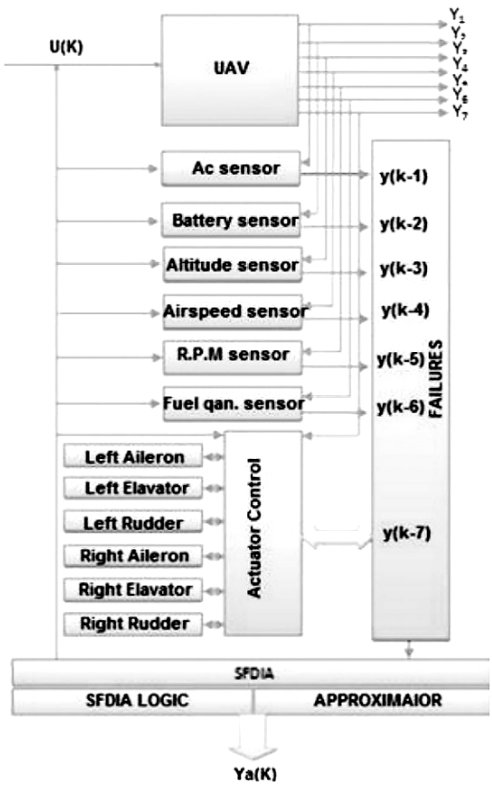


Fig. 4. Bank of estimators for output residual generation

1. **Approximators**

The block contains the Neural Network based function estimators. Fig. 5 is a scheme for estimation of (6) types of faults. It includes Ac. Generator sensor channel (k), sensor channel $b(K)$, altitude sensor channel $c(K)$, air speed sensor channel (K), RPM sensor channel (k), fuel quantity sensor channel $f(k)$ [22, 23].

2. **SFDIA LOGIC**

The block performs the main threshold based sensor failure detection identification and accommodation operations (Fig. 5). Two filtered residuals (derived by filtering the absolute approximation error with both a "fast" low pass filters and a "slow" low pass filter) are contemporary evaluated for each sensor.

When the fast filter output is bigger than a threshold, the corresponding NN learning is preventively stopped (LE=0), in order to prevent the possibly wrong signal from being learnt. When the slow filter output is bigger than a threshold, the corresponding sensor is declared failed (AE=0), so the accommodation logic is enabled, and the estimated signal is fed back through the controller instead of the faulty one [24].

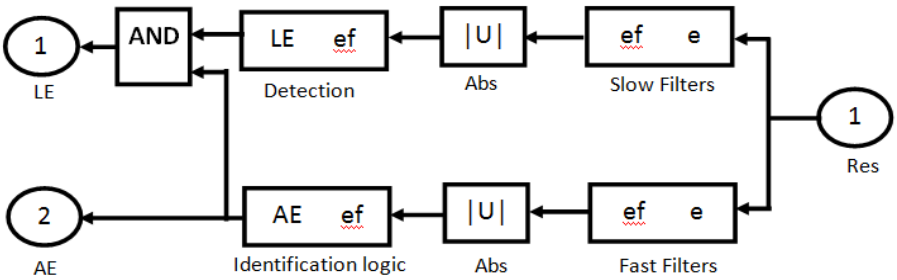


Fig. 5. SFDIA Logic

4. Results

In order to apply this technique (ANN based SFDIA)and(NN) trained with the (EMRAN) algorithms (Extended Minimal Resource Allocation Network) which is a set of conditions that decide how the (EMRAN) structure should be adapted to better suit the training data to improve electrical sources performance of unmanned airborne vehicles seven cases were taken in this study as follows:

4.1 The altitude and airspeed sensor

Figure (6-a) and (6-b) show a typical time of Y_{1-} (altitude and airspeed sensor) and its estimation, during the occurrence of a simulated failure on it, at (t_f =300 sec) using the (EMRAN) algorithm, [25, 26]. The results show that EMRAN-algorithm is well suited for fast on-line identification of nonlinear plants.

4.2 The (R.P.M) and fuel quantity sensor

Figure 7a and 7b shows a typical time of Y_{2-} (R.P.M) and fuel quantity sensor) and its estimation, during the occurrence of a simulated failure on it, at (t_f =300 sec).

4.3 The Ac generator and battery sensor

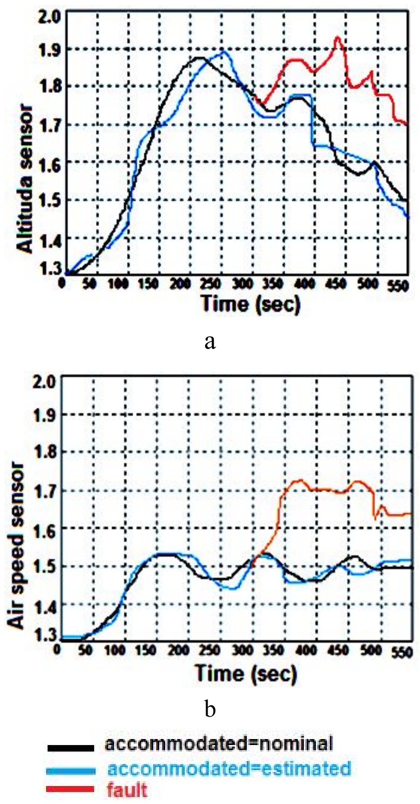
Figure 8a and 8b show a typical time of Y_{4-} (**Ac generator and battery sensor**) and its estimation, during the occurrence of a simulated failure onit, at (t_f =300 sec).

4.4 The (pitch, roll and heading angle) sensors

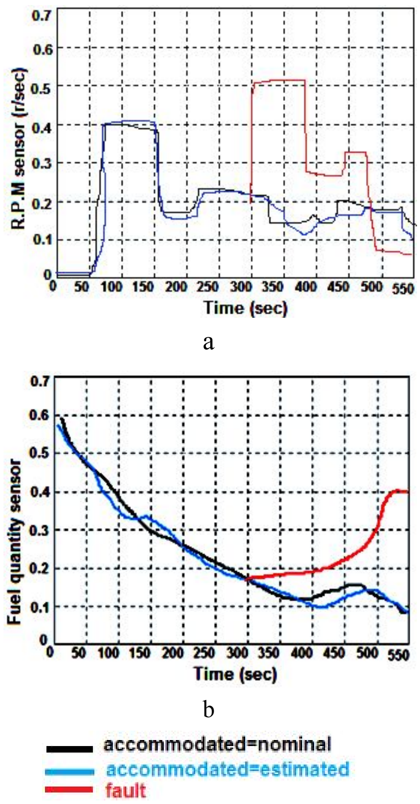
Figure 9a, 9b and 9c show a typical time of Y_{3-} (**pitch angle, roll angel and heading angle sensor**) and its estimation, during the occurrence of a simulated failure on it, at (t_f =300 sec).

4.5 The (aileron, rudder and elevator) deflection sensor

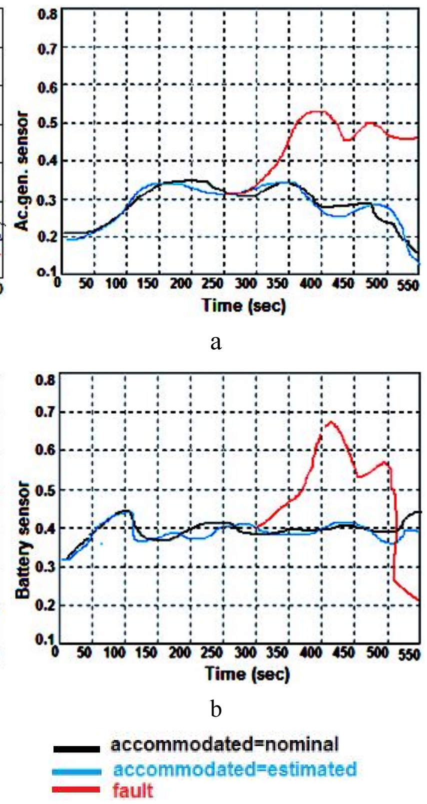
Figure 10-12 show typical time of (Aileron, Rudder and Elevator) angle and its estimation, during the occurrence of a simulated failure on it, at t_f= 50 sec.



Fig/ 6. Altitude (a) and airspeed (b) sensor (accommodated nominal, accommodated estimated, failed) at (t_f = 300 sec)



Fig/ 7. R.P.M (a) and fuel quantity (b) sensor (accommodated nominal, accommodated estimated, failed) at (t_f = 300 sec)



Fig/ 8. Ac generator (a) and Battery (b) sensor (accommodated nominal, accommodated estimated, failed) at (a – t_f = 350 sec, b – t_f = 300 sec)

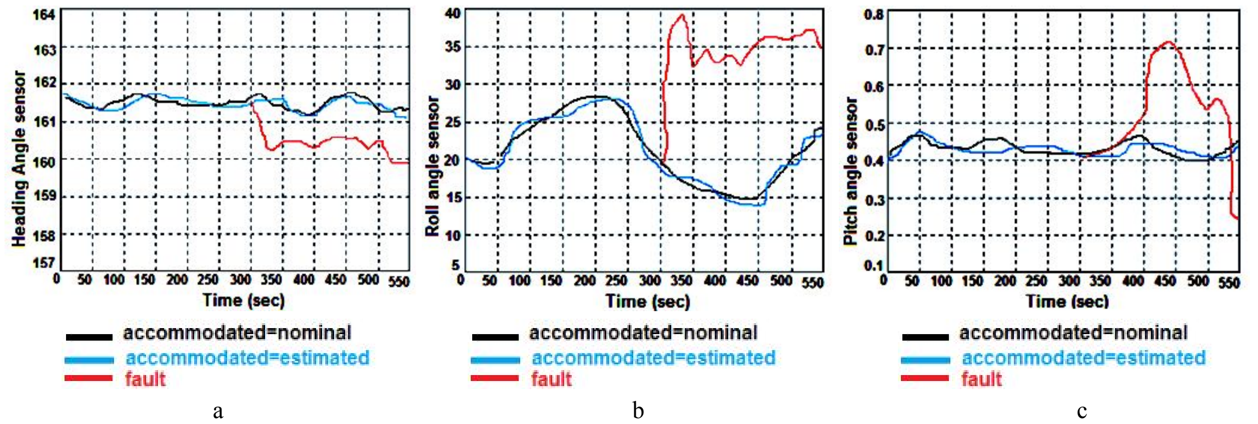
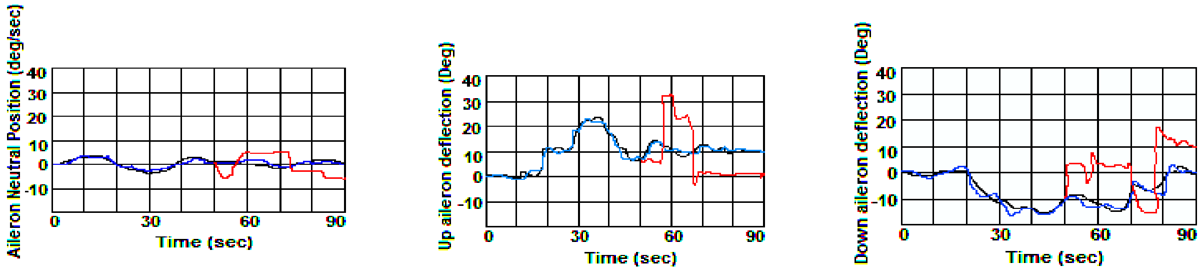


Fig. 9. Heading angle sensor and its estimation, during the occurrence of a simulated failure on it (a); roll (b) and pitch (c) angel sensor (accommodated nominal, accommodated estimated, failed) at (t_f = 300 sec)

These figures show that when fauilt takes place the trend will no more follow the normal behavour trend.hence, it can be detected early.inspection can then locate the cause and solution can be put to prevent eccedents.

Conclusions

In this paper unmanned air vehicle (UAV), Neural Network based tool scheme (SFDIA) for the Sensor Failure, Detection, Identification and Accommodation problem tool were analyzed. The scheme was implemented with (RBF-EMRAN Neural Network algorithms which are a set of conditions that decide how the (EMRAN) structure should be adapted to better suit the training data. The use of Neural Network for sensor estimation of a parameter of interest has been studied. By analysis the results of applying the technique used in this research, the application showed high-resolution for the process of replacing the faulty sensor by using the Neural Network estimated value itself for further usage (as a feed back). Close match between estimation and actual sensor output has been established. In addition the capabilities of (SFDIA) are a consequence of the extensive modularity of the whole simulation tool. It allows an easy change of unmanned air vehicle (UAV), dynamics and feedback control law as well as Neural Network (NN) estimators and (SFDIA) scheme.



a b c

Fig. 10. The aileron deflection sensor signal with time at $t_f = 40$ sec (a – up, b – neutral, c – down)

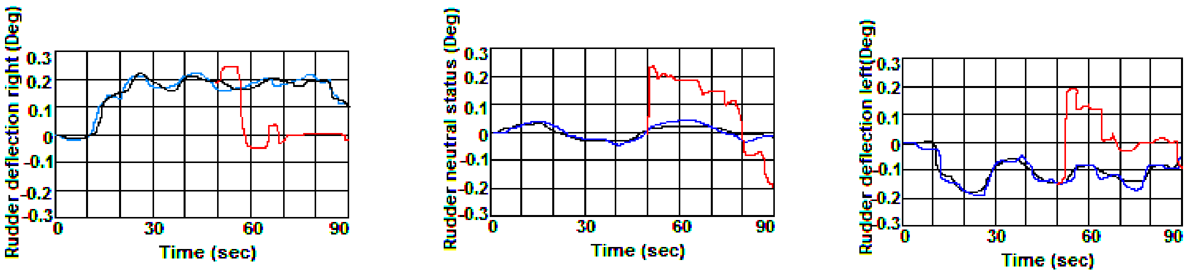


Fig. 11. The Rudder deflection sensor signal with time at $t_f = 40$ sec (a – left, b – neutral, c – down)

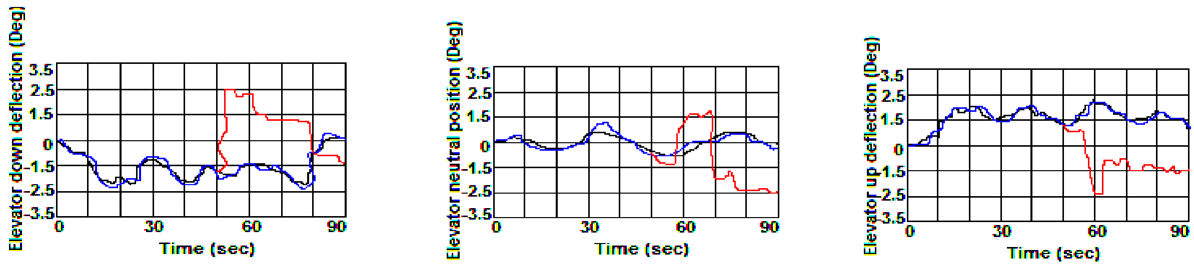


Fig. 12. The Elevator deflection sensor signal with time at $t_f = 40$ sec (a-up, b – neutral, c – down)

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Збільшення ефективності польоту безпілотних літальних апаратів з використанням штучних нейронних мереж

Сааді Т. Курді, Ахмед Хамід Рея, Ал-Ашматі Акрам Фаті Хуссейн

Мета. Відомо, що політ безпілотного літального апарату (БПЛА) здійснюється за допомогою датчиків, які передають роботу БПЛА, і на основі цієї інформації БПЛА контролюється і дає їм замовлення, необхідні для виконання завдання польоту БПЛА. Несправності в управлінні відбуваються під час польоту БПЛА, відповідно до концепцій авіації - критична ситуація, яка впливає на завершення місії. Ці несправності викликані головним чином збоєм в датчиках, які можна розділити на ситуації з польотом – про політ літальних апаратів (напрямок, висота, повітряна швидкість, вертикальна швидкість і кут атаки) і ситуація з управлінням польотом, це стосується поверхонь управління польотом, таких як кермо, елерон, кермо відхилення і датчики перемикача і регулятора висоти. У цій статті представлений ефективний метод, що дозволяє датчикам працювати з високою ефективністю. **Методи.** У цій роботі використовуються два різних підходи. Перший підхід заснований на інструменті на основі нейронної мережі для моделювання, симуляції та аналізу літаків, збою датчиків; виявлення, ідентифікації і рішення проблем. Другий підхід - нейронна мережа, що навчається за допомогою алгоритмів, представляє собою набір умов, які визначають, як структура мережі повинна бути адаптована, щоб краще відповідати даним навчання. **Результати.** Результати моделювання та аналізу датчиків літальних апаратів показали, що інструменти на основі нейронної мережі і алгоритми здатні показувати результати з високою роздільною здатністю щодо поведінки датчиків і, отже, поведінки БПЛА. **Висновки.** Можливості інструмента є наслідком великої модульності всієї системи моделювання. Це дозволяє легко міняти безпілотні літальні апарати, закони динаміки і контролю зворотнього зв'язку, а також оцінки нейронної мережі.

Ключові слова: безпілотний літальний апарат; виявлення несправностей датчиків; діагностика несправностей; моделювання та симулювання літальних апаратів.

Увеличение эффективности полета беспилотных летательных аппаратов с использованием искусственных нейронных сетей

Саади Т. Курди, Ахмед Хамид Рея, Ал-Ашмати Акрам Фати Хуссейн

Цель. Известно, что полет беспилотного летательного аппарата (БПЛА) осуществляется с помощью датчиков, которые передают работу БПЛА, и на основе этой информации БПЛА контролируется и дает им заказы, необходимые для выполнения задачи полета БПЛА. Неисправности в управлении происходят во время полета БПЛА, в соответствии с концепциями авиации – критическая ситуация, которая влияет на завершение миссии. Эти неисправности вызваны главным образом сбоем в датчиках, которые можно разделить на ситуации с полетом – о полете летательных аппаратов (направление, высота, воздушная скорость, вертикальная скорость и угол атаки) и ситуация с управлением полетом, это касается поверхностей управления полетом, таких как руль, элерон, руль отклонения и датчики переключателя и регулятора высоты. В этой статье представлен эффективный метод, позволяющий датчикам работать с высокой эффективностью. **Методы.** В этой работе используются два разных подхода. Первый подход основан на инструменте на основе нейронной сети для моделирования, симулирования и анализа самолетов, сбоя датчиков; обнаружения, идентификации и решения проблем. Второй подход – нейронная сеть, обучаемая с помощью алгоритмов, которая представляет собой набор условий, которые определяют, как структура сети должна быть адаптирована, чтобы лучше соответствовать данным обучения. **Результаты.** Результаты моделирования и анализа датчиков летательных аппаратов показали, что инструменты на основе нейронной сети и алгоритмы способны показывать результаты высокого разрешения в отношении поведения датчиков и, следовательно, поведения БПЛА. **Выводы.** Возможности инструмента являются следствием обширной модульности всей системы моделирования. Это позволяет легко менять беспилотные летательные аппараты, законы динамики и контроля обратной связи, а также оценки нейронной сети.

Ключевые слова: беспилотный летательный аппарат; обнаружение неисправностей датчиков; диагностика неисправностей; моделирование и симулирование летательных аппаратов.