Improvement Sensors Work of Unmanned Air Vehicles Using Artificial Neural Networks Based SFDIA

Saadi T. Kurdi¹, Ahmed Hameed Reja²

¹,² Electromechanical Engineering Department, University of Technology, Baghdad-Iraq

Abstract— This paper presents an efficient technique to ensure that the sensors can operate with high efficiency. Two different approaches are used in this work, the first one is Neural Network (NN) based Sensor Failure Detection Identification and Accommodation (SFDIA) and the other is Neural Network trained with the Extended Minimal Resource Allocation Network (EMRAN). The results showed that the modeling process of neural network-based tool SFDIA and the algorithm EMRAN are able to show the high-resolution sensors in the behavior of control surfaces of the aircraft (Roll, pitch, heading angle, aileron deflection, rudder deflection and elevator deflection) sensors and the diagnosis of repair systems.

Keywords—Unmanned air vehicle (UAV); Neural Networks (NNs); Sensor fault detection (SFD); Fault diagnosis; Aircraft sensors

I. INTRODUCTION

Unmanned air vehicle (UAV) are complex technical system and it is out of reach of the pilot (operator). That means it needs an operator 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 in Unmanned vehicle that transmit the required data 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 based tool sensor failure, detection, identification and accommodation (SFDIA) 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

DOI: 10.24128/IJRAER.2017. EF56rs
situation), and the second stage is Extended Minimal Resource Allocation Network (EMRAN) algorithms which is a set of conditions that decide how the EMRAN structure should be adapted to better suit the training data, using (MATLAB, Simulink) and Extended-MRAN (EMRAN) algorithms.

II. NEURAL NETWORK-BASED SFDIA

Analytical redundancy implies that some of the system variables are functionally related by a variable \( y(k) \) and can be expressed as a function of a suitable set of other variables \( Z(k) \) and input commands \( U(k) \) as predicted in Figure 1.

\[
y_s(k) = f[z(k), u(k)]
\]

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) [13].

\[
r(k) = y(k) - y_s(k)
\]

When the square of this (filtered) residual exceeds predefined threshold, the state of the corresponding sensor is declared suspect and a suitable procedure is recall to decide situation of this sensor. Figure 2 shows a flowchart of the predefined threshold.

![Figure 1. Neural Network SFDIA [12]](image)

![Figure 2. Flowchart of the predefined threshold](image)
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 (see Figure 3).

$$y_a(k) = r(k)$$

**Figure 3. The accommodation with the estimation given by the ANN**

There is 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 accommodation) [17].

### III. THE SIMULATION

The Neural Network based SFDIA modeling and simulation toolbox was built through using MATLAB and simulink for technical computing (by Math works Inc.) [18]. In particular the freely available aircraft SFDIA toolbox for MATLAB provides powerful tools for aircraft simulation [19], [20]. A bank of output estimators has been implemented as in Figure 4.

### IV. SENSOR FAILURE DETECTION IDENTIFICATION AND ACCOMMODATION (SFDIA)

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

**A. Estimators (Approximators)**

The block contains the (Roll, Pitch, Heading, Aileron deflection, Rudder deflection and Elevator deflection) Sensors. A bank of output estimators ($y_1$ to $y_4$) was simulated as showed in Figure 4 which is built under the Simulink (by The Math works Inc.) [22], [23].

**B. SFDIA Logic**

SFDIA logic performs the main threshold based sensor failure detection identification and accommodation operations (see Figure 5). Two filtered residuals (derived by filtering the absolute approximation error with both a “fast” and “slow” low pass filters, LPFs) 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].

![Figure 4. Bank of estimators for output residual generation (Y1 to Y4)](image-url)

V. RESULTS

In order to apply this technique ANN based SFDIA and NN trained with the EMRAN algorithms which is a set of conditions that decide how the (EMRAN) structure should be adapted to get better suit training data so as to improve electrical sources performance of unmanned air vehicles. There is four cases were taken in this study as follows:

A. Pitch Angle, Roll Angle, and Heading Angle Sensors

Figure 6 (a, b, and c) shows a typical time of pitch angle, roll angle, and heading angle sensors and its estimation during the occurrence of a simulated failure on its at t of 300 sec.
Figure 6. Typical time of (a) pitch angle sensor, (b) roll angle sensor, (c) heading angle sensor
B. The Rudder Deflection, Aileron Deflection, Elevator Deflection Sensors

1. Aileron Deflection Sensor

Figure 7 (a, b and c) shows the aileron deflection sensor signal as function of time at $t_f = 40$ sec. They show that aileron deflection up, aileron neutral position, aileron deflection down.

![Figure 7. Aileron typical time of (a) deflection up, (b) neutral position, (c) deflection down.](image)

2. Rudder Deflection Sensor

Figure 8 (a, b and c) show the Rudder deflection sensor signal with time at $t_f = 40$ sec. Its show that rudder deflection sensor right, rudder neutral position, rudder deflection sensor left.

![Figure 8. Rudder deflection sensor (a) rudder deflection sensor right, (b) rudder neutral position, (c) rudder deflection sensor left](image)

3. Elevator Deflection Sensor

Figure 9 (a, b and c) show the Elevator deflection sensor signal with time at $t_f = 40$ sec. they show that Elevator deflection up, Elevator neutral position, Elevator deflection down, respectively.

![Figure 9. Elevator deflection sensor (a) elevator deflection up, (b) elevator neutral position, (c) elevator deflection down](image)
From Figures above, when fault takes place the trend will no more follow the normal behaviour trend. Hence, it can be detected early. Inspection can then locate the cause and solution can be put to prevent excursions. Figure 10 showing the location of Aileron, Rudder, and Elevator on the aircraft.

**Figure 10. Locations of (Aileron, Rudder, Elevator) on the aircraft**

**VI. 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 feedback). 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.

**REFERENCES**