A SCHEME OF SFDIA USING MULTILAYER PERCEPTRON AND EBP FOR UNMANNED AERIAL VEHICLE

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ABSTRACT: In modern complex high performance aircraft systems, safety is one of the important factors to be considered for better fulfillment of any mission. This can be achieved by using fault tolerant control system (FTCS) to detect, identify, and accommodate for any type of failure that occur during flight. The major faults that can occurr in aircrafts are sensor, actuator, control surface and other structural damages. Amongst these, sensor fault detection, identification, and accommodation (SFDIA) is considered as an important issue, particularly when measurements from a faulty sensor are used in feedback loop of control law. Since aircraft control law use sensor feedback to establish current dynamic state of the airplane, even slight sensor inaccuracies, if left undetected, can lead to closed loop instability, leading to unrecoverable damages.

In this paper, the design and implementation of a neural network (with online training) based SFDIA scheme used for unmanned aerial vehicle (Aerosonde) is discussed. Here in this study only rate sensors [1] are considered because of their vital role in flight control system. In the presence of small fault sometimes the error between sensor measurements and neural network estimation will be small leading to the sensor being considered as a healthy sensor despite a fault in it. In this paper, the existing SFDIA algorithm in [2] is modified to handle such type of fault by introducing a threshold named $\text{FAILURE}_{\text{limit}}$, which is the number of iterations to wait before placing a sensor from failed state to nominal state. The SFDIA (see fig.1 for the architecture) is achieved by using a Main Neural Network (MNN) and *n* Decentralized Neural Network (DNN) for a system with *n* sensors assumed to be without physical redundancy. The outputs of MNN are estimates of *n* sensors being considered at time 'k' using feedback signals from time instant 'k-1' to 'k-m'. The output j-th DNN is the estimate of j-th sensor at time instant 'k' and the inputs are the measurements from any number up to 'n-1' sensors; i.e., all the *n* sensors excluding the j-th one. The neural networks have an input layer, hidden layers, and an output layer trained by using Extended Backpropagation (EBP) algorithm. The activation function used here is three degree of freedom sigmoidal activation function, which is having three parameters that can be varied to get infinite number of limits and zero crossing slopes. These parameters are upper bound, lower bound, and temperature. In the updating phase of EBP, the weights, biases and the parameters of activation function are adjusted to minimize the mean square error based on steepest descent method. The MNN and DNN outputs for roll rate sensor in the presence fault is shown in fig.2

The SFDIA scheme used in this paper monitors three states of sensor health called nominal, suspect and failed states. This can be achieved by setting five different thresholds, which limits different quadratic estimation errors. These are MQEE_{max} which limits Main Quadratic Estimation Error, OQEE_{max} which limits Output Quadratic Estimation Error, DQEE_{max} which is higher limit for Decentralized Quadratic Estimation Error, DQEE_{low} which is lower limit for DQEE and $\text{SUSPECT}_{\text{limit}}$ which limits the number of iterations, a sensor may remain in suspected health. MQEE is the measure of failure between MNN estimates and feedback data sent to the flight control computer, OQEE is the measure of failure between MNN and DNN estimates and DQEE is the measure of failure between DNN estimates and sensor measurements. MQEE better detects "step type" faults and OQEE is good for detecting "ramp type" faults. DQEE is used for identifying the faulty sensor. The MQEE and DQEE for roll rate sensor is shown in fig.2.

The SFDIA detects a failure when either MQEE rises above $MQEE_{max}$ or OQEE rises above $OQEE_{max.}$ Identification is done by using double threshold, $DQEE_{low}$ and $DQEE_{max}$. If DQEE for a particular sensor is less than $DQEE_{low}$ is considered as in nominal health state and if it is in between DQEElow and $DQEE_{max}$ is moved to suspected state. If the sensor remains in suspected state for iterations more than $SUSPECT_{limit}$ is moved to failed state. A sensor whose DQEE exceeds both $DQEE_{low}$ and $DQEE_{max}$ is also placed in failed state. A sensor, which is in failed state, cannot come back to suspected state even if its DQEE is less than $DQEE_{max}$, but can come back to nominal health state if its DQEE comes below $DQEE_{low}$. Transition from suspected state to nominal health state is also possible.

In accommodation stage if the sensor is in nominal health state, the sensor outputs are feeding back to flight control computer and DNN continues its learning. If the sensor is in suspected state, still SFDIA allows the output of the sensor to be sent to the flight control computer, but the learning for the sensor's DNN is halted. The SFDIA prohibit of sending the output of failed sensor to flight control computer and stops learning of DNN for that particular sensor. The DNN estimate is sent instead. The learning of MNN is always enabled in all states of sensor failures, which is learning from feedback signal sent to the flight control computer. The SFDIA stage is implemented separately for different sensors of interest.

The paper highlights the application of Neural Network for the detection, isolation and reconfiguration of faults in rate sensors of unmanned aerial vehicle. In the final paper, algorithm will be evaluated with different types of sensors faults.

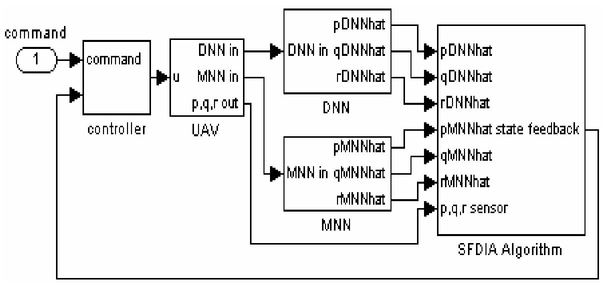

Fig. 1: Block Diagram of SFDIA using MLP NN with EBF training

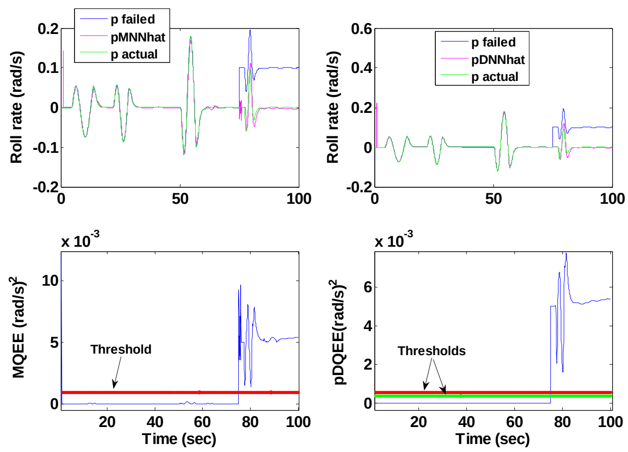

Fig. 2: MNN and DNN outputs for roll rate SFDIA

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