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SYSTEM HEALTH MANAGEMENT OF SAFETY CRITICAL SYSTEMS USING ARTIFICIAL NEURAL NETWORKS

*,[1]Sreelakshmi, E. S., [2]Krishnaprasad, R., [3]Dr. Manju Nanda and [4]Jayanthi, J.

[1]Electronics and Communication Engineering Department, MES College of Engineering, Kuttipuram
[2, 3, 4]Aerospace and Electronics Division, CSIR-National Aerospace Laboratories, Bangalore

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ABSTRACT

Safety critical systems are the systems which defines the safety and monitors the system performance based on some safety criterions. A system health management (SHM) system monitors the safety critical system while it is in operation, and thus is able to detect faults, as soon as they occur. In this paper we propose an approach to determine the system health using artificial neural network. Unmanned Aerial Vehicle is used as a case study to demonstrate the SHM approach using ANN. Artificial Neural Networks (ANN) is one of the powerful technique which helps to predict the functionality modes of a UAV and can also be used to classify the data. The system can be implemented as two important stages as neural network predictor and classifier. The MATLAB R2014. A neural network tool box is using here because it can easily meet our requirements of prediction and classification of neural networks. Even there are various critical sub systems are available in UAV safety critical systems, the considering sub system is sensor subsystem. At the output stage, by observing the performance of classifier, we obtain the idea about whether the system is healthy or not.

INTRODUCTION

System health management is one of the important type under Fault Detection Isolation and Recovery (FDIR). The FDIR methods finds various different applications in various domains (Inseok *et al*., 2010), these domains include chemical engineering, nuclear engineering, aerospace engineering, automotive systems etc. The implementation of these systems will be different from one to another. Unmanned Aerial Vehicles (UAVs) are the important scope of aerospace engineering in which the system health management finds great application (Lennon *et al*., 2001). UAVs find applications in various fields of operations such as cargo services, geographic studies, remote sensing and mostly in the powerful defense area of a nation. Inside a UAV itself, there are various subsystems which needs the continuous monitoring of its health and making necessary decisions on its operation (Iman and Youmin, 2011). It includes actuator subsystem, plant, sensor subsystem etc. Sensor system is an important sub system of UAV because it is responsible for the efficient monitoring of the all its operations (Dimitry *et al*., 2008). The sensor subsystem is considering. Even various sensor subsystems are available, the sensor system includes gyro sensor, differential pressure sensor, pressure and speed sensor, angle of attack sensor and altimeter. In SHM each sensor is identifying with its parameters which controls its output values. Artificial Neural Networks (ANN) is a powerful tool in classification, prediction of different data sets. The data set obtained from sensor sub system can be analyzed with ANNs (Rory Telford and Stuart Galloway, 2015). Even though various SHM techniques are available (Lei Xu and Jiuping Xu, 2014), based on challenges of the FDIR techniques in particular subsystem one should design its own specific procedures for overcoming the problems (Sghairi *et al*., 2008). Here various functionality modes of UAV is to be analyzed with the help of scenarios of different UAV sensors. By importing the data set which is required to train the neural network, it can be used for further stages of processing like prediction and classification of current state of subsystem. The simulated results after the implementation can be used to enable the whole UAV system to bring itself out of the trouble if it is occurred. So the performance of the system determines

Corresponding author: Sreelakshmi, E. S.
Electronics and Communication Engineering Department, MES College of Engineering, Kuttipuram.

the efficiency of the future of the entire UAV system. The paper is organized in to five sections including background works, proposed approach, implementation of the system, simulation results and scope and conclusion.

Background work

FDIR methods includes several levels of technical procedures, mainly include residual generation and residual classification (Hiroaki Nakanishi and Koichi Inoue, 2013; Hatzipantelis *et al*., 1995). Artificial Neural Networks (ANNs) are widely applied nowadays for classification, identification, control, diagnostics, recognition, etc. They can be implemented for identification of dynamic systems. The concept of ANN is highly used in design and simulation of control system of Unmanned Aerial Vehicles (UAVs) (Hatzipantelis *et al*., 1995; Bhaskar Prasad Rimal *et al*., 2009). VERTEX, THEANO are the basic neural network tool boxes that are available. Still it have some compatibility problems with our requirements the MATLAB 2014.a is used as a tool box for artificial neural network. The THEANO and VERTEX are some of the best tools for artificial neural networks in deep learning process. The applications of such systems includes logistic regression, multilayer perceptron and deep convolutional networks. Python is the basic language used for coding the THEANO and VERTEX tool. Because of this, it may cause some difficulty in designing of neural network system for one who coming from electronics background. Here the MATLAB artificial neural network tool box is used. Different types of applications are available with the neural network toolbox of the MATLAB. The versions of MATLAB after MATLAB R2013.b include variety of applications to solve some specific problems of neural networks (Hiroaki Nakanishi and Koichi Inoue, 2013; Hatzipantelis *et al*., 1995). MATLAB R2014.a is considering here. This is an important platform to perform artificial neural network solutions with the help of some applications. It includes neural net fitting, clustering, pattern recognition, neural network time series response etc. The MATLAB finds great application in almost all works of artificial intelligence because of its easiness to handle and availability of the various tutorials.

Proposed approach

The health management of any system deals with the continuous health monitoring of that particular system. Here the sensor sub system with multiple number of sensors are considering and health monitoring is done by observing the parameters that affects the sensor outputs. Here five sensors are considered, these are the basic sensor parts of any UAV system. Gyro sensor, differential pressure sensor, pressure and speed sensor, angle of attack sensor and accelerometer are considering here. The sensor parameters are given to a neural network in which the health condition can be analyzed. As in fig.1, the neural network involves two important stages, the neural network predictor and the neural network classifier. The neural network predictor predicts the values of the parameter values of a sensor that is possible to it. The predicted values can be given to the next stage, which is a neural network classifier. Neural network classifier will classify the sensors as healthy and unhealthy sensors. The decision making stage will make a decision in such a way that the health condition of the sensor can be analyzed further. This stage is consisting of simple decision making statements which will take the output of classifier stage to make a decision.

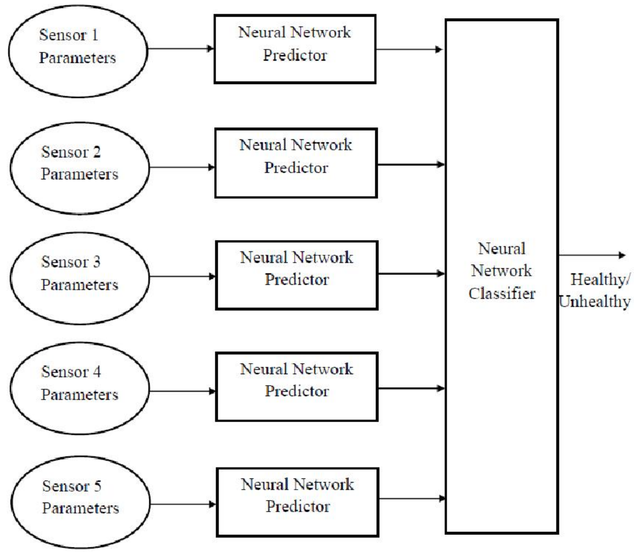

Fig. 1. Block Diagram

Implementation of proposed approach

The implementation of proposed system involves various steps. The selection of an UAV subsystem to work is the primary thing. As the unmanned aerial vehicle system is considering, one can note that there are various subsystems are there. Out of the several available subsystems the sensor subsystem forms an important role in UAV system design. Various sensors are available in an aircraft system. It may ranges from simple temperature sensors to gyro sensors. Considering such a sensor subsystem one can work on the health management of the system. Here a five sensor subsystem is considering, which includes gyro sensor, differential pressure sensor, speed and direction sensor, accelerometer and angle of attack sensor. Since the fault tolerant system is highly susceptible to any small change in its inputs, one should take care of selecting the inputs of such a system. There are different steps involved in designing of such a health monitoring system. The neural FDI scheme, will be developed and employed to perform the detection (residual generation) and isolation (residual classification) tasks of the diagnostic system using two different structures of neural networks.

Residual Generation

Fault detection or residual generation task represents the key part in FDI algorithm. The fulfillment of this task is depending mainly on the modelling of the dynamic behavior of the monitored process, which can be performed by constructing a Dynamic Neural Network (DNN). The constructed neural networks, is called neural residual generator, should have the ability to identify all known modes of operations under healthy and faulty conditions. Three main operations are performed in a neuron structure. First, the weighted sum of the inputs is calculated according to the expression:

$$x(k) = \omega^T u(k) = \sum_{p=1}^{P} \omega_p u_p(k) \quad (1)$$

where ω denotes the input-weight vector, P is the number of inputs, and u(k) is the input vector. The next step is giving these values to a residual classifier section. But here in health monitoring of sensor subsystems the residual generation step can be done using Neural network Predictors.

Residual Classification

Isolation task can be done by evaluating the generated residual signals from the neural observer, and each residual can be treated as pattern referred to a specific fault. So that the problem of fault isolation can be seen as pattern recognition or pattern classification; the idea beyond the residual evaluation is to extract fault information from the residual itself in order to know which fault has happened and when. The isolation methodology can be fulfilled using a simple and non-complicated structure of Learning Vector Quantization (LVQ) network as an adaptive (static) neural network classifier which provided detailed information about the occurrence time and the location of each simulated fault. Neural network classifiers can work in this step for residual classification.

Learning and Training of Neural Networks

A five sensor subsystem is considering here, in which we need to consider about the parameters that drive each sensor's outputs. Each sensor have five or six such parameters which will drive its output. Bias, Scaling factor, sensitivity, quantization and random walk noise are some of the parameters that drive the gyro sensor outputs. Similarly for all other sensors we can chose a particular number of parameters out of several available parameters. For the neural network predictor one can give these parameters as input and delayed version of these as targeted outputs. Predictor will predict the upcoming values for these parameters by considering its inputs and targeted outputs. Generally LMA (Levenberg Marquardt alogorithm) can be used for training of neural network predictor. LMA is used to solve nonlinear least square problems, to find the local minimum. The primary application of the Levenberg–Marquardt algorithm is in the least squares curve fitting problem: given a set of m empirical datum pairs of independent and dependent variables, $(\boldsymbol{x_i}, \boldsymbol{y_i})$, optimize the parameters β of the model curve f(x, β) so that the sum of the squares of the deviations:

$$\boldsymbol{S(\beta)} = \sum_{i=1}^{m} (\boldsymbol{y_i} - \boldsymbol{f}(\boldsymbol{x_i}, \boldsymbol{\beta}))^2 \quad (2)$$

The predictor predicts the upcoming values of sensor parameters by minimizing the error between the current output and the targeted output. This is termed as backward propagation of a neural network. In the next stage of process the predicted output is given to the neural network classifier, which can classify the sensor parameters to a nominal range as well as to a faulty range. Along with the predicted values target class is also required for the training of a neural network classifier. Here the target class means, two classes: a healthy class and an unhealthy class. The classifier classifies all of it's inputs in to either a healthy class or to an unhealthy class. SCG (Scaled conjugate gradient) algorithm is used for back propagation. SCG is a supervised learning algorithm for feed forward neural networks, and is a member of the class of conjugate gradient methods. Each iteration k of a CGM (conjugate gradient method computes $\boldsymbol{w_i}$ where $\boldsymbol{R^N}$ is a new conjugate direction, and

$$\boldsymbol{w_{k+1}} = \boldsymbol{w_k} + \boldsymbol{\alpha_k} \cdot \boldsymbol{p_k} \quad (3)$$

is the size of the step in this direction. Actually $\boldsymbol{p_k}$ is a function of $\boldsymbol{\alpha_k}$ the Hessian matrix of the error function, namely the matrix of the second derivatives. In contrast to other CGMs which avoid the complex computation of the Hessian and approximate $\boldsymbol{\alpha_k}$ with a time-consuming line search procedure, SCG makes the following simple approximation of the term $\boldsymbol{E^n}(\boldsymbol{w_k})$ a key component of the computation of $\boldsymbol{\alpha_k}$.

SIMULATION RESULTS AND DISCUSSION

The health management of safety critical system is done using artificial neural network predictors and classifiers. Sensor subsystem constitutes five sensors whose parameters are given to neural network predictor section for generating upcoming values of these parameters. Confusion matrix helps one to analyze the results. Confusion matrix for the sensor subsystem is shown below for various types of data sets. In this Figure, Fig. (2), there are four confusion matrices. Out of these we need to look the last all confusion matrix. All other three matrices evaluates internal system performance. Those deals about the training, validation and testing of the data. In the all confusion matrix first two diagonal cells show the number and percentage of correct classifications by the trained network. For example 3 parameters are correctly classified as healthy. This corresponds to 1.9% of all 158 given inputs. Similarly, 78 cases are correctly classified as unhealthy. This corresponds to 49.4% of all data. 1 of the unhealthy data are incorrectly classified as healthy and this corresponds to 0.6% of all 158 parameters in the data. Similarly, 76 of the healthy parameters are incorrectly classified as unhealthy and this corresponds to 48.1% of all data. Out of 4 healthy predictions, 75% are correct and 25% are wrong. Out of 154 unhealthy predictions, 50.6% are correct and 49.4% are wrong. Out of 79 healthy cases, 3.8% are correctly predicted as healthy and 96.2% are predicted as unhealthy. Out of 79 unhealthy cases, 96.7% are correctly classified as unhealthy and 1.3% are classified as healthy. Overall, 97.6% of the predictions are correct and 2.4% are wrong classifications. From this we can understand that the system for given set of sensor parameter values are unhealthy.

Similarly by analyzing the Fig. 3, we can understand that it is a confusion matrix is for partially healthy system since there is a small percentage of difference between parameter classification in to nominal range and into faulty range. The Fig.4 shows the system is healthy, which means the safety critical system with that input set is a healthy system. The Fig.5 shows the performance of a neural network classifier for classifying given set of data. In this example the number of iterations is six and best performance of such system will reach at sixth epoch. The performance can have variations depending upon each classifications.

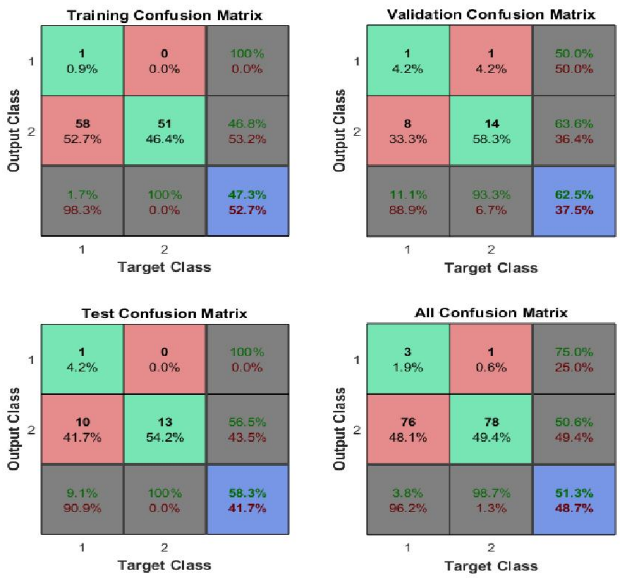

Fig.2. Confusion Matrix of an Unhealthy System

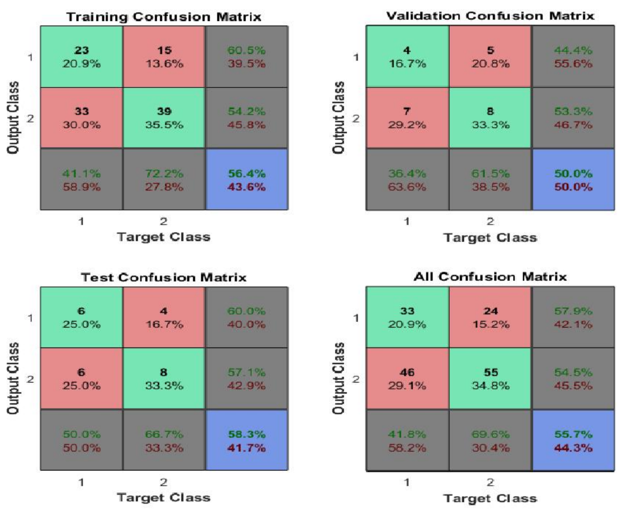

Fig.3.Confusion Matrix for a partially healthy system

Fig.4. Confusion Matrix for a healthy system

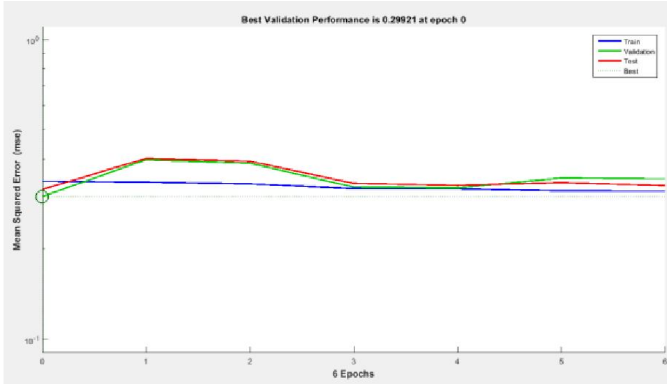

Fig.5. Performance plot of classifier

Conclusion

Health system management are those systems whose failure could result in loss of life, significant property damage, or damage to the environment. Many modern information systems are becoming safety-critical in a general sense because financial loss and even loss of life can result from their failure. It is because of these reasons the system health management of a UAV is that much important. Here the health monitoring of an important safety critical system in an unmanned aerial vehicle is done using artificial neural network is done. By using this, the health of such a system can be analyzed, which means whether the system is healthy, partially healthy or unhealthy. As a scope of this technique we can say that by using deep neural networks which consist of more number of hidden layers than a common artificial neural network the performance can be increased.

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