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Developing Validation and Test Data for Flight Control Sensor

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ABSTRACT

Validation is a process carried out after training to determine the degree of validity of a measuring device. In flight control process, Flight Control Sensors (FCS) are used to identify objects, obstacles and other spacecraft in flight during a flying session. There are primary and secondary flight control units or sensors. In developing the sensors, some parameters need to be monitored namely, Parameters of the analysis model, Imputed values and parameters of the imputation models and Random effects. Training, validation and testing are carried out in the order of 60%, 20% and 20%, respectively. In all machine learning models, validation set is used to train the parameters of a model while test set is used to evaluate the performance. Validation set is used to tune the hyper parameters. Especially in cases where over fitting is to be mitigated, validation is carried out. Results show the training representation and the level of sensitivity of the FCS in use.

Keywords: *Validation, Flight Control Sensor, Hyper Parameters, Over fitting*

Introduction

Validation is the means of determining the degree of validity of a measuring device or equipment. In the context of this presentation, it is the next process after training and is followed by testing. There can only be validation after training since without training, there can be no validation and hence, no testing. Validation and testing are desirable because in machine learning technique, we have what is called supervised and unsupervised learning. Supervised learning is similar to human learning from experience. But since computers, and by extension, neurons or neural networks, have no experience, there is need to provide previous data, called training data, as a substitute. An analogy is the process of learning from a teacher hence the name supervised learning. Conversely, unsupervised learning involves using clustering algorithms to discover and determine data clusters. The aim is to organize data into groups (or clusters) where similarity exists among members in a group and are distinct from members in other groups. The foregoing underscores the need for validation and testing after a successful training process.

In aircraft flight control parlance, there are primary and secondary flight control units or sensors. The primary flight controls are used during flight operations to control an aircraft safely. They consist of the ailerons, elevators and rudder. Secondary flight control systems are the flap control, slate control, ground spoiler control and trim control. There are sensors that control these systems. This research is aimed at developing validation and test data for the sensors that actuate the flight control surfaces or systems. After a successful design of the sensor that enables the flight control system, there is need to validate and test the designed model for efficient use to ensure aircraft safety during flight.

Review of Relevant Literature

The reviews hereby presented are meant to show the high points of validation process using appropriate test data in research settings. The works of erudite scholars in this field are hereby reviewed and presented for a better knowledge of the subject under study.

Aruneshwaran, et al (2012) in a Neural Adaptive Back-Stepping Flight Controller for A Ducted Fan UAV Whose Dynamics Is Characterized By Uncertainties And Highly Coupled Nonlinearities, proposed that neural adaptive back-stepping controller could handle unknown nonlinearities, unmodeled dynamics and external wind disturbances. The neural controller parameters were adapted online using Lyapunov based updated laws. Ducted fan UAVs was used to perform both the operations of aircrafts and helicopters, thus opening up a wide range of applications. This review was applied in handling unstable and highly coupled dynamics of the ducted fan UAV which presented challenges in stability and control of the vehicle in transition and forward flight. The mathematical model of the ducted fan UAV along with the neural adaptive back-stepping controller was implemented in the MATLAB/SIMULINK environment. The simulation used 100 hidden layer neurons in the radial basic function neural network (RBFNN). The major problem with the research was that it required multiple designs and applications of neural adaptive back-stepping controllers each to track the roll, pitch and yaw commands respectively. This multiplicity presented limitations.

Yavuz Sarı (2014), did a work titled Performance Evaluation of the Various Training Algorithms and Network Topologies in a Neural-network-based Inverse Kinematics Solution for Robots. In the work, it was stated that training algorithm and network topology affect the performance of the neural network. Several training algorithms were used in neural networks. The effect of various learning algorithms on the learning performance of the neural networks on the inverse kinematics model learning of a seven-joint redundant robotic manipulator was investigated. The Levenberg-Marquardth (LM) algorithm was found to be significantly more efficient compared to other training algorithms. The effect of the various network types, activation functions and number of neurons in the hidden layer on the learning performance of the neural network were then investigated using the LM algorithm. Among different network topologies, the best results were obtained for the feedforward network model with logistic sigmoid (logsig) activation function and 41 neurons in the hidden layer. The results were presented with graphics and tables.

The paper by M. Belcastro et al (2004) first discussed the challenges imposed on current regulatory guidelines for aviation software. Subsequently, technologies being researched by NASA and others were discussed as they focused on various aspects of the software challenges. These technologies include the formal methods of model checking, compositional verification, static analysis, program synthesis, and runtime analysis. Some validation challenges for adaptive control, comprising proving convergence over long durations, guaranteeing controller stability, using new tools to compute statistical error bounds, identifying problems in fault-tolerant software, and testing in the presence of adaptation were presented. The presentation of these specific challenges was in the context of a software validation effort in testing the Integrated Flight Control System (IFCS) neural control software at the Dryden Flight

Research Center. Lastly, the challenges to develop technologies to help prevent aircraft system failures, detect and identify failures that do occur, and provide enhanced guidance and control capability to prevent and recover from vehicle loss of control were briefly cited in connection with ongoing work at the NASA Langley Research Center.

The above reviews are meant to guide in the implementation of this research.

Methodology

The flow chart for the implementation of this work is shown in Figure 1.0.

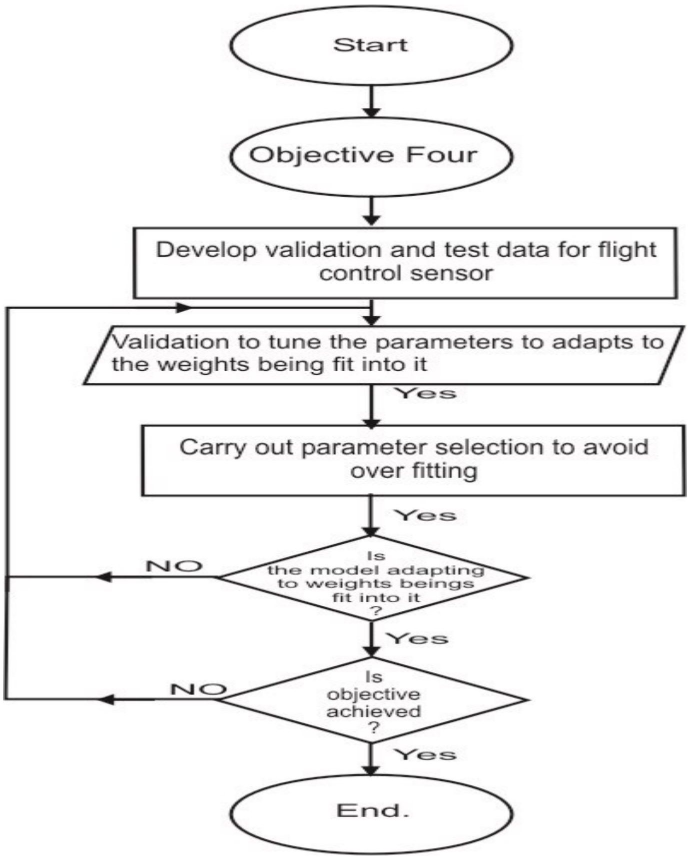

Figure 1.0 Flowchart for this work

Figure 1.0 presents the flowchart for the actualization of the task of this work. Here, it is required to develop validation and test data for flight control sensor so as to make the parameters to adapt to the weights being fit into it. It is also meant to carry out parameter selection to avoid over fitting after the training process. Figure 2.0 shows the model used for the validation and test as required. Further discussion on this is made during presentation of results.

Parameter Selection

The procedure used to specify which parameters to monitor and display in the results is as follows:

The following parameters are monitored:

a. ⍰ Parameters of the analysis model.
b. ⍰ Imputed values and parameters of the imputation models.
c. ⍰ Random effects
d. ⍰ Other parameters.

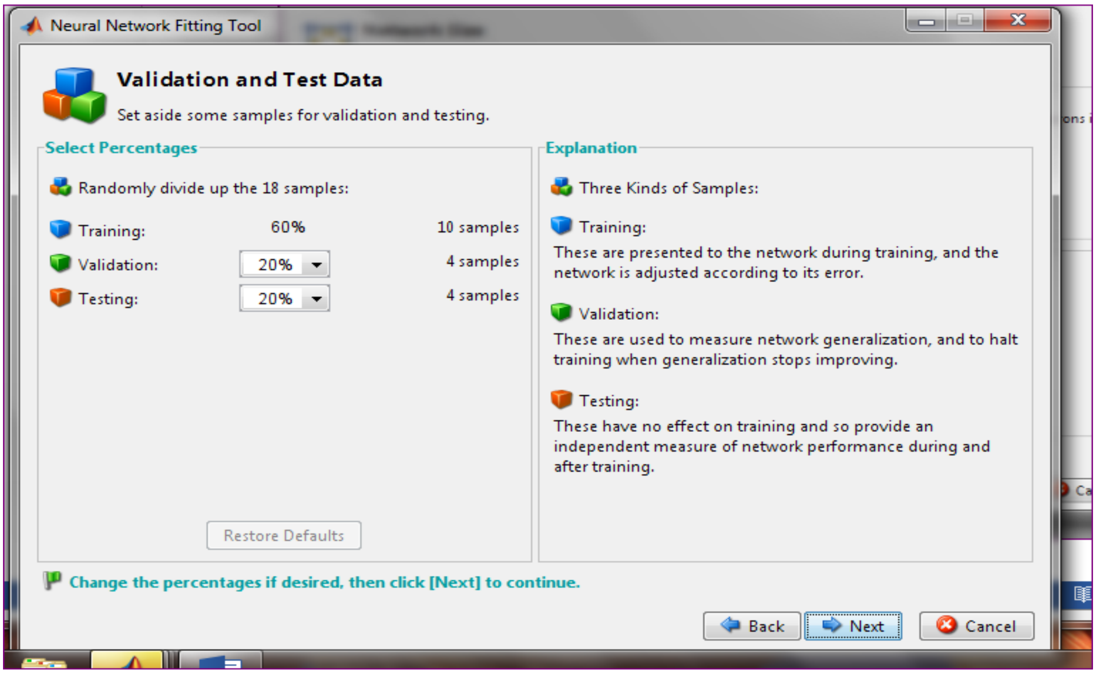

Figure 2.0: Developed validation and test data for a flight control sensor

Figure 2.0 Shows developed validation and test data for flight control sensor. It shows the result of eighteen samples used for the training. From the result, it is seen that the training was 60%, validation, 20% and testing 20%. The result of using these eighteen samples in training the validation and test data is clearly shown during presentation. It should be noted that validation set is different from test set. While validation set can actually be regarded as part of training set because it is used to build our model, neural networks or others, it is usually used for parameter selection and to avoid over fitting. This is especially so because our model is nonlinear, being a neural network. Thus, if trained only on a training set, it is most likely to attain 100% accuracy and hence, over fit. This results to a very poor performance on test set. This necessitates the need for a validation set, independent from the training set, to be used for parameter selection.

Put succinctly, validation set is used to train the parameters of a model while test set is used to evaluate the performance. These are not particularly specific for NN. They are used for almost all machine learning models.

To summarize the above process, we have it as follows:

Training set… to fit the parameters (i.e., weights).

Validation set… to tune the parameters (i.e., architecture).

Test set… to assess the performance (generalization and predictive power).

The objective is to develop Validation and Test Data for Flight Control Sensor. This developed validation and test data for flight control sensor is shown in Figure 2.0. There can only be validation after training since without training, there can be no validation and hence, no testing. Validation and testing are desirable because in machine learning technique, we have what is called supervised and unsupervised learning. Supervised learning is similar to human learning from experience. But since computers, and by extension, neurons or neural networks, have no experience, there is need to provide previous data, called training data, as a substitute. An analogy is the process of learning from a teacher hence the name supervised learning. Conversely, unsupervised learning involves using, clustering algorithms to discover and determine data clusters. The aim is to organize data into groups (or clusters) where similarity exists among members in a group and are distinct from members in other groups. The foregoing underscores the need for validation and testing after a successful training process.
In this presentation, eighteen samples are used for the training. From the developed sensor, training, validation and testing are in the following order:
Training - 60%

Validation - 20%

Testing - 20%

Training is meant to fit the parameters, also known as weights as explained further where the process of training was discussed. Thereafter, validation is meant to tune the parameters, that is, the architecture, to adapt to the weights being fit into it. Finally, testing is carried out to assess the performance of the entire system by way of generalization and predictive power. The reason for the allotment of percentage to training, validation and testing in the manner above is to ensure that the rules are adhered to, that is, so that the process s**ticks to the rule**s. That is why it has to be carried out severally compared to validation and testing.

Specifically, validation set is used to train the parameters of a model, while test set is used to evaluate the performance. These are not particularly specific for Neural Network. They are used for almost all machine learning models. The developed validation and test data for flight control sensor is shown in Figure 2.0 while the result is plotted in a graph shown in Figure 3.0 for eighteen samples of the validation and test data.

The eighteen (18) samples used are randomly divided in the ratio of 60:20:20. For convenience, the order is as follows:

Training 60% 10 samples

Validation 20% 4 samples

Testing 20% 4 samples

Considering that the training process has been carried out vide objective three already discussed, the validation process is carried out as presented in the percent discourse in order to measure network generalization and to halt training when generalization stops improving. Thereafter, testing is carried out and these have no effect on training as it is meant to provide an independent measure of network performance during and after the training process has been carried out. The result of the trained eighteen samples of the validation and test data are plotted in Figure 3.0.

Result Presentation and Analysis

The results realized in this work is hereby presented and analyzed. Normally, a verification exercise is carried out as a process in which it is desired to test or verify a given design against a set specification before being manufactured. However, validation is a process involving the testing of a manufactured design to ensure that it meets all functional and electrical or control precision. Validation is carried out as a technique in order to assess the effectiveness of a model, especially is cases where there is need to mitigate over fitting. It is also used to determine the hyper parameters of a model so as to find out which parameters will yield lowest test error.

Considering that a flight control sensor is a highly sensitive mechanism, the training data set is used to construct a predictive relationship between aircraft flight conditions and actual control operations. In a situation where a model being trained has a set of hyper parameters, such as a neural network, these parameters could be the learning rate or the number of iterations during training. The training set is used to train the model given a set of hyper parameters. The validation set is used to set the values for the hyper parameters. This is another way of saying that the validation set is used to evaluate the performance of the model for the different combinations of hyper parametric values. Figure 3.0 shows a plot of trained eighteen samples as explained.

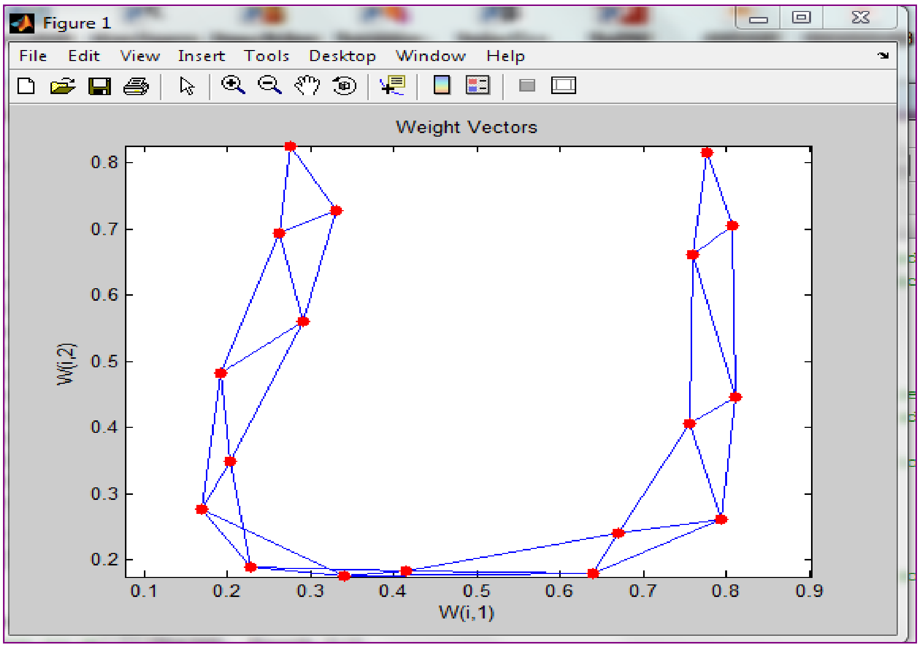

Figure 3.0 ***The result of the trained eighteen samples of the validation and test data***

This graph shows the weight vectors of the samples.

Summarily, validation set is used to select a model while test set is used for assessing model performance on future data. The more the samples used and allocated for validation and testing, the better the performance of the designed model, though the samples should not be such that will over fit during training. However, in many applications, only two sets are created namely, training set and test set.

The test set creates room for the comparison of different models in an unbiased way. This is because test data are different from validation set data which are part of the training and hyper parameter selection process.

Conclusion

It has so far been shown in this paper that data where a model is trained on is called a training set. Validation set is data the model has not been trained on used to tune the hyper parameters. Finally, test set is similar to the validation set but differs slightly as it is used when the model has been customized. Flight control sensors provide fly-by-wire systems' position and load status information with reliability and redundancy. Cockpit controls and flight control systems are so designed that they provide means of adjusting, controlling and monitoring aircraft altitude during flight to maintain high level safety. There is need to develop this control measure during the design and manufacturing stage. The control tower plays an important role in coordinating the overall control of an aircraft during flight by monitoring the flight control sensors accordingly.

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