Data-driven Fault Detection of Un-manned Aerial Vehicles Using Supervised Learning Over Cloud Networks*

Parsa Yousefi
Member, IEEE
Electrical and Computer Engineering Department
University of Texas, San Antonio
San Antonio, Texas, USA
parsa.yousefi@utsa.edu

Hamid Fekriazgomi
Electrical and Computer Engineering Department
University of Texas, San Antonio
San Antonio, Texas, USA
hamid.fekriazgomi@utsa.edu

John J. Prevost, PhD
Member, IEEE
Electrical and Computer Engineering Department
University of Texas, San Antonio
San Antonio, Texas, USA
jeff.prevost@utsa.edu

Mo Jamshidi, PhD
Fellow, IEEE
Electrical and Computer Engineering Department
University of Texas, San Antonio
San Antonio, Texas, USA
mo.jamshidi@utsa.edu
mojamshidi4@gmail.com

***Abstract*—Modern applications of Unmanned Aerial Vehicles are increasingly attracting the attention of traditional safety and reliability fields. There exist many standard approaches for determining UAV fault detection. However, there doesn't exist a method that is not only model independent but also has the ability to detect faults which have not been predefined for the UAV system. In this research we present two supervised machine learning algorithms implementing Logistic Regression and Liner Discriminant Analysis of Algorithms, respectively, to predict UAV faults. The data which has been used for these approaches comes from discrete-sampled, de-noised analog signals based on the voltage and current inputs belonging to four actuators of the UAV drones. In addition, we demonstrate that by using a five-fold cross validation process to generate different types of training and test datasets, the optimized model can be selected. We verify our results through an analysis describing the accuracies of our proposed model.**

***Keywords*—Un-manned Aerial Vehicles, Signal-based Fault Detection, Machine Learning, Supervised Learning, Data Prediction, Linear Discriminant Analysis, Logistic Regression.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) are recently playing undeniable roles in many aspects of engineering [1]. Their significance is related to being valuable source of data for inspection, surveillance, mapping, and 3D modeling issues. The term "UAV" is used commonly in the geomatics community, but other terms like drone, remotely piloted vehicle (RPV), remotely operated aircraft and unmanned combat air vehicle are often used as well [2]. Latest generation of UAVs will be constructed to achieve their mission not only with increased efficiency, but also with more safety and security [3]. In addition, for all aspects of engineering systems such as vehicle dynamics, autonomous vehicles, chemical processes, manufacturing systems, power networks, electric machines and industrial electronic equipment, low cost and reliability are essential factors. As a result, the condition monitoring of UAVs should be considered in order to guarantee reliability while ensuring operational efficiently [4].

Fault Detection, Isolation, and Recovery (FDIR) is a category in Control Systems and Systems Identification which concentrates on monitoring systems in the presence of a fault [5]. The term "fault" refers to any internal or external error in the system. Using FDIR, observers can locate the source and the position in which the fault is happening, and they can diagnose it in a timely manner. In all UAV applications, if there exists a mechanism to predict and detect the occurrence of the fault, it may increase reliability and minimize the cost of maintenance through early discovery. The source of faults in the UAVs are categorized as internal or external, e.g. failure in a computation processor and any disturbance by an external source, respectively. There are many approaches in the detection and diagnosis of UAVs faults. These methods could be considered in three different categories: model based, knowledge based and data driven approaches.

The main advantage of the model based approaches is their accuracy. However, based on their way of construction makes them not reasonable to implement. In other words, these methods highly rely on the accuracy of the developed model. This need of modelling accuracy leads us to have a cost-inefficient process. In addition, for the online fault detection process, model based algorithms are not the best choices.

The knowledge based approaches are based on the perception of the system performance. Officially it refers to the approaches that rely on some IF-THEN rules that are extracted from different working conditions. These kinds of approaches are highly efficient when considering the predefined faults of the system, and they are also reasonable from the financial point of view. The main disadvantage of these kind of approaches are related their inability of detecting new faults which have not been experience on the knowledge extraction stage [6].

The data driven approaches, generally, concentrate on the gathered information by any feedback loop from the system [7].

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In these methods, using statistical and mathematical functions and operations, the data can be analyzed using machine learning algorithms or deep neural networks. The most beneficial advantage of data-based fault detection models is independency from the original model of the system.

One category in machine learning for statistical analysis of information is Supervised Learning which refers to training the machine with sets of input-output pairs [8]. The inputs are the general data received from the sensors, and the outputs are the labels. In fault detection theory of UAVs, the labels can be defined as "faulty" and "healthy". The purpose of this family of learning algorithms is to train a model based on the inferred data and their corresponding labels, and to predict the labels of a new set a data for evaluation and testing. Two generative algorithms in this category are Linear Discriminant Analysis (LDA) and Logistic Regression [8-10].

As an extended algorithm of Fisher [11] and a generative model, LDA is a binary classification method for finding a linear pattern between all the features from the data and predicting the labels for future data [12]. In LDA, in training section, by definition of a dependent variable which is a linear combination of all elements from feature vector, a linear boundary with the minimum error between two classes would be generated, and in evaluation part, any independent data would be analyzed to determine to which class they belong. Also, as another method in binary classification, Logistic Regression method can be used for estimation of the binary probability for each member of the data regarding its corresponding label. It is essential to say that in both models the output of the training is to minimize a cost function (also known as cross entropy) which is negative log likelihood function.

In [4], Lashkari et al. have presented a neural network (NN) approach to detect the induction motor stator fault diagnosis. In fact, they have worked on a knowledge-based method to acquire a proper data based to detect stator inter-turn winding fault. In addition, in [13], a database has been constructed which is resulted from the induction motor modelling while running in the healthy and faulty mode to extract the main features of each situations. Using this database, they have trained their NN [4] and Fuzzy [13] to work in the real time condition. Their work consists of knowledge that are extracted from the data derived by the modelling in an offline stage.

In [14] the authors proposed the approach which is related to process variable selection and time–lagged features. For achieving LDA, da Silva et al. [14] have used Successive Projection Algorithm (SPA). The basic SPA has been extended to have larger focus relevant feature selection. The main advantage of the method introduced in [14] is the reduction of sensors needed to detect a fault. This reduction in the number of sensors has the noise rejection advantage. And also, fault isolation has not been viewed in their work.

In [15], Li et al. have proposed a two-stage LDA structure for fault detection in building chiller systems, and Multi-class objects have been formulated through the aforementioned classification problem. The advantage of this proposed method is to reduce the data dimension. Using this approach, the fault could be detected as the monitored data is similar to one of the predefined clusters and also the severity of fault will be determined based on the trained severity level. The real time monitoring and diagnosis is one of the challenge that has not been considered in this work.

In [16], Sun et al. have proposed a data-driven Kalman Filter based on Adaptive Neuro Fuzzy Inference System (ANFIS) framework for the UAV sensor fault detection. In fact, it integrates the data driven detection cycle with the Kalman filter residuals. The mentioned method has two main advantages: the first one is the independency from the model and the second one is its adaptive rules which are extracted from updated training databases.

In [17], Pandya et al. have used Multinomial Logistic Regression (MLR) in fault diagnosis of rolling element bearing. MLR is a generalized linear model that uses logistic curve modelling to fit the probabilistic occurrence of an event. In [17] it has been shown that the MLR method in fault detection process is much more effective than the traditional Neural Network (NN) and Support Vector Machine (SVM) approaches. In addition, Pandya et al. [17] verified that the computational time in MLR is smaller compare to the conventional Artificial Neural Networks (ANN) and SVM as the other advantage.

From the literature above, although there are lots of model-based, knowledge-based and data-driven approaches being applied in UAVs or other systems' fault detection, the main disadvantage of model-based methods is the dependency on defining the mathematical model of the systems which causes additional effort and expense. On the other hand, the knowledge-based and data-driven methods are independent from the modeling exercise, but these approaches may not be efficient dealing with faults which are not predefined for the detector system. Accordingly, this paper presents a new approach which combines the positive features of the mentioned approaches. Also, by proposing a method without the need of modeling, simply being based on the observed data, this approach has the capability of predicting the future data to detect any occurrence of external fault in the drone systems. This prediction task could even enable us to have proper fault detection in the cases that our occurred fault has not been defined before.

II. Methodology

This paper mainly concentrates on data classification using machine learning [18] —especially supervised learning [8]— approaches. The main dataset which was used in this paper, is discretely generated from a de-noising module of analog input voltages and currents of four rotors in a drone belongs to mini parrot family. As it can be seen in Figure 1, four pair signals (voltage-current actuator signals) has been captured from the drone in two trajectories with the same initial and final positions – one without and one with external fault. After de-noising all signals using envelope detector, with the sample rate of $250\frac{sample}{sec}$, the dataset has been generated in 1,000 epochs.

For implementing Machine Learning models on the dataset, first, the feature vector has been generated with the dimension of $\underbrace{4}_{Number\ of\ rotors} \times \underbrace{2}_{voltage-current} = 8$ and the total number of data-points in the dataset is 1,000—for avoiding overfitting, each epoch is considered one data-sample. Furthermore, this is reasonable that the dimension of each data sample is $4 \times 2 \times 250$. The general block diagram of machine learning approach in this paper is shown in Figure 2.

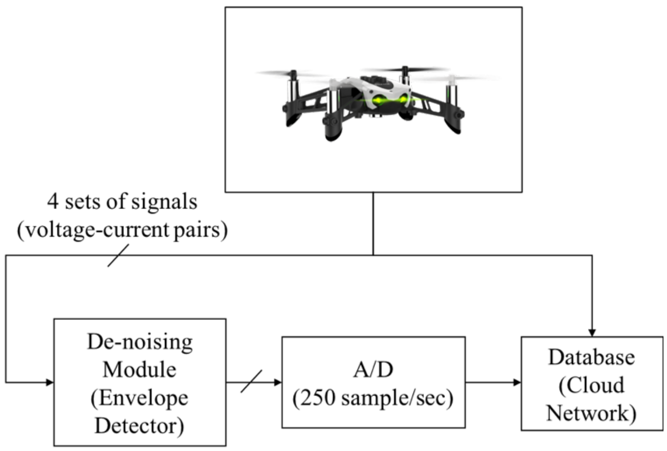

Figure 1: Block Diagram for Generating Dataset from actuator signals of the drone

This paper has used some definitions and notations regarding ML algorithms used as follows:

- Data: x which is the feature vector
- Labels: $y \in \{"Faulty", "Healthy"\}$
- Prior Distribution $\left\{P\left(\underbrace{y}_{labels}\right)\right\}$ which is the probability of unknown (labels) before any observation on data
- Likelihood Function $\left\{P\left(\underbrace{\vec{x}}_{data} \mid \underbrace{y}_{labels}\right)\right\}$ which is the probability of data given labels which can be modeled as a Gaussian distribution.
- Posterior Distribution $\left\{P\left(\underbrace{y}_{labels} \mid \underbrace{\vec{x}}_{data}\right)\right\}$ which is the probability of labels given data, and this distribution would be used for decision making.

a. Linear Discriminant Analysis (LDA) approach for decision making [9, 10, 19]

By using this method and the mentioned definitions, the optimal solution using Bayes rule are shown in (1) – (4).

$$(\vec{x}-\vec{\mu}_0)^T\Sigma_0^{-1}(\vec{x}-\vec{\mu_0}) + \ln|\Sigma_0| - (\vec{x}-\vec{\mu}_1)^T\Sigma_1^{-1}(\vec{x}-\vec{\mu}_1) - \ln|\Sigma_0| \gtrless \theta \quad (1)$$

$$\vec{w}.\vec{x} \gtrless c \quad (2)$$

$$\vec{w} = \frac{1}{2}(\Sigma_0 + \Sigma_1)^{-1}(\vec{\mu}_0 - \vec{\mu}_1) \quad (3)$$

$$c = \frac{1}{2}(\theta - \vec{\mu}_0^T\Sigma_0^{-1}\vec{\mu}_0 + \vec{\mu}_1^T\Sigma_1^{-1}\vec{\mu}_1) \quad (4)$$

In the mentioned inequalities and equations, (μ, Σ) are the mean and covariance parameters of the distribution regarding each label, and θ, c are the thresholds. Furthermore, the posterior distribution would be calculated regarding the Bayes rule.

b. Logistic Regression (LR) approach for decision making [8-10, 19, 20]

Using this method, the posterior distribution would be calculated based on sigmoid function, "Maximum a Posteriori" theory (MAP), and the following expressions.

$$P\left(\underbrace{y}_{labels} \mid \underbrace{\vec{x}}_{data}\right) = \sigma(z) = \frac{1}{1+e^{-z}} \quad (5)$$

$$\frac{P(y=\text{"Faulty"} \mid \vec{x})}{P(y=\text{"Healthy"} \mid \vec{x})} = e^z \gtrless \theta \quad (6)$$

$$z = \vec{w}^T.\vec{x} + w_0 \gtrless c \quad (7)$$

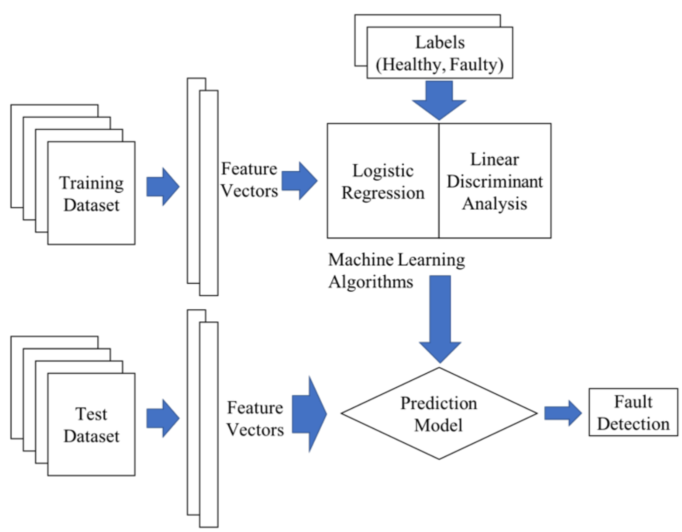

Figure 2: Block Diagram of Fault Detection Model

III. Results

Referring to Figure 2, In the training section, 80% of the data has been fed for training and 20% of remaining data has been used for validating the model. Using 5-fold cross validation, the dataset has been divided into five equal sections, and each of which has been used for Test Dataset in five model trainings. Table 1 shows the pattern of each fold for data usage, and equations (8) and (9) show the cross entropy for optimizing the negative log of likelihood function in LR.

$$\vec{\theta} = \arg\max\{P(training\ data \mid validation\ labels)\} \quad (8)$$

$$J(\vec{\theta}) = -E_{x,y} \log\{P(y \mid x, \theta)\} \quad (9)$$

Table 1: Training and Test data

Fold No	Portion of original data in the Training	Portion of original data for Validation
0	1st, 2nd, 3rd, 4th- one-fifth	5th one-fifth
1	1st, 2nd, 3rd, 5th- one-fifth	4th one-fifth
2	1st, 2nd, 4th, 5th- one-fifth	3rd one-fifth
3	1st, 3rd, 4th, 5th- one-fifth	2nd one-fifth
4	2nd, 3rd, 4th, 5th- one-fifth	1st one-fifth

Using each of aforementioned models, the Receiver Operating Characteristic (ROC) curves for showing True "Faulty" vs. False "Faulty" are shown in Figure 3 and Figure 4. Furthermore, the Area Under the Curve (AUC) for each model, specificities, and sensitivities are shown in Table 2 and Table 3.

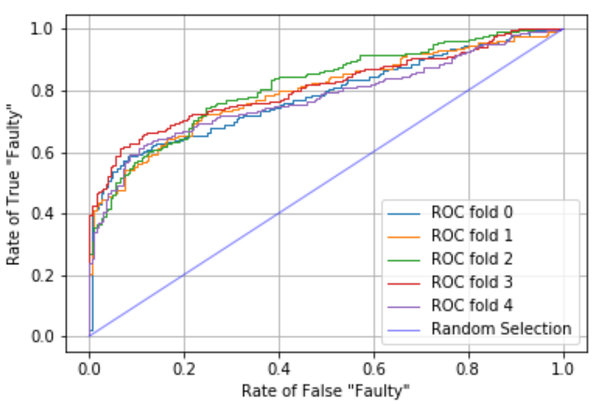

Figure 3: ROC plot of the data classification using LR

Table 2: Results of data classification using LR

Result / Fold	True "Healthy" rate	True "Faulty" rate	True Threshold	AUC (Accuracy)
0	0.805	0.640	0.570871	0.77
1	0.780	0.685	0.488921	0.77
2	0.845	0.615	0.545806	0.80
3	0.795	0.705	0.454084	0.80
4	0.805	0.665	0.524325	0.79
Average	0.806	0.662	0.5168014	0.786

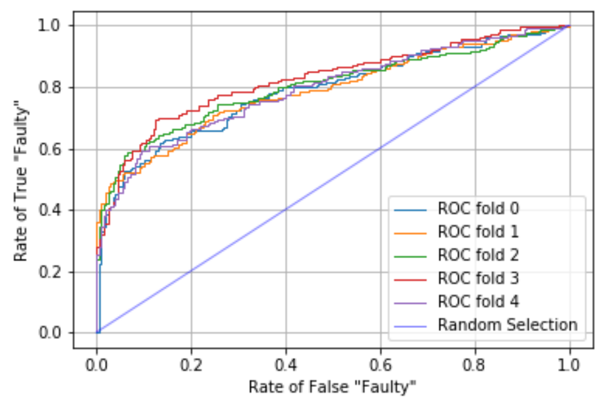

Figure 4: ROC plot of the data classification using LDA

Table 3: Results of data classification using LDA

Result / Fold	True "Healthy" rate	True "Faulty" rate	True Threshold	AUC (Accuracy)
0	0.825	0.640	0.510578	0.82
1	0.775	0.670	0.506437	0.77
2	0.815	0.670	0.490307	0.81
3	0.785	0.725	0.455055	0.75
4	0.765	0.675	0.464323	0.81
Average	0.793	0.676	0.48534	0.792

Table 2 shows that the probability of sensitivity has the average value of 0.806 while the specificity average value is 0.662. Also, the thresholds in each fold are in the range of

$0.51 \pm std$, and the total area under the curve (accuracy) has an average value of 78.6% which is highly the effect of nonlinear sigmoid function. Referring to Table 3, it shows that the Logistic Regression has a better accuracy—average value of 79.2%—for predicting the labels in each class for test data while the average Sensitivity, 0.793, has higher value and the average specificity, 0.676, has lower value comparing to LDA, respectively. The better result using this algorithm is due to the fact that the thresholds, $0.48 \pm std$, are less than the average thresholds in LR.

Conclusion

In this paper, we proposed a new data-driven approach for the fault detection and diagnosis of UAVs. In other data driven fault detection works, there are multiple problems with prediction as described earlier. Combining the advantages of the traditional model-based approaches and knowledge-based approaches leads us to use the prediction-based data driven method to accurately detect and diagnosis UAVs faults. Although this data driven method is a model independent approach, it has the ability to predict undefined faults. This is the main reason of its high accuracy in different working conditions.

As supervised machine learning approaches have demonstrated prediction capabilities, we have implemented Logistic Regression and Linear Discriminant Analysis algorithms. The data used for the training part came from the de-noised analog sampled signals based on voltage and current signals of the drone four actuators. Fitting the above-mentioned models to this data and by means of a five-fold cross validation process, we used 80 percent of the data in the training stage and other 20 percent to test the designed model. This allows our model to achieve an average accuracy of 78.6% for the LR and 79.2% for the LDA models, respectively.

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