Detection of turbulence-type anomalies from in-flight data using learning models guided by flight physics

Charles DAMPEYROU [1,2], Martin GHIENNE [1], Anita DEHOUX [2], Jean-Luc DION [1]

[1]Laboratoire QUARTZ, ISAE-Supméca, 93400 Saint-Ouen, France
[2]Aquila Data Enabler, 47 Rue Louis Blanc, 92400 Courbevoie, France
charles.dampeyrou@isae-supmeca.fr

1 Introduction

Atmospheric turbulence has a significant impact on airplane motions. It can induce excessive stress and fatigue damage, shortening the aircraft lifespan. The identification of turbulence in aircraft service phase is of particular interest to estimate actual structural fatigue or to improve maintenance plans. Different methods exist to identify turbulence from in-board aircraft data. A common detection method is the use of the vertical component of air speed with regard to the ground to identify potential turbulence. This method is highly dependant on the incidence angle sensors accuracy, and is considering an identical airspeed over the entire plane. Cornman et al. calculate the aircraft's response to vertical gusts from its structural characteristics [1]. They use the response function and acceleration measurements to estimate the intensity of turbulence, approximated by a Von Kármán spectrum . Li et al. proposed a method to detect turbulence using an isolation forest algorithm on aircraft sensor data [2]. Turbulence can indeed be investigated using anomaly detection techniques, since its occurrence is low in relation to the complete flight data and since it significantly modifies aircraft behavior. In their survey [3], L. Basora, *et al.* classifie them into the following families of methods. Anomalous data can be detected using clustering, by identifying data that does not belong to any cluster. Distance metric between data samples can help identifying outliers. Statistical methods provide the probability of outcome of a particular data sample. Reconstruction methods and prediction methods rely on a model which reconstruct the data or predict the next sample. These models struggle on samples which differs from the majority of the data, which allow to find anomalies. Recently, deep learning models have shown that they can perform well in detecting anomalies in temporal series, with reconstruction models [4], predictive models [5] and models computing the "reconstruction probability" [6].

In this work, an hybrid model is proposed to detect turbulence. This model reconstructs the flight dynamics equations. The lift, drag and lateral force coefficients are modeled using deep learning techniques in an unsupervised way. The proposed model only requires data measured by the aircraft in-board instruments. The principle of this approach is based on the assumption that the equations terms will be better reconstructed during steady flight than during turbulence.

The combined use of machine learning and domain-specific equations is commonly known as Scientific Machine Learning, generally achieved by integrating a complementary loss function during model training [7].

The paper is organized as follow. The methodology is first presented in section 2. The datasets used are presented in section 3, as well as the methodology to evaluate the model.

2 Methodology

We consider Stengel's notation [8] for the equations of flight. Introducing the load factor J to substitute the acceleration, the flight dynamics equations can be written as :

$$\begin{pmatrix} T\cos\xi - D\cos\alpha\cos\beta - Q\cos\alpha\sin\beta + L\sin\alpha \\ D\sin\beta - Q\cos\beta \\ -T\sin\xi - D\sin\alpha\cos\beta - Q\sin\alpha\sin\beta - L\cos\alpha \end{pmatrix} = m\begin{pmatrix} J_x \\ J_y \\ J_z \end{pmatrix} \tag{1}$$

where α is the incidence angle, β the sideslip angle, ξ the angle between the thrust and the plane's x-axis, T the thrust component, D the drag component, Q the lateral force component, L the lift component and J_x, J_y and J_z the components of the load factor in the aircraft's frame. The aerodynamic forces are defined by (2)

$$\begin{pmatrix} D & Q & L \end{pmatrix}^T = \frac{1}{2}\rho V^2 \begin{pmatrix} SC_D & S_yC_Q & SC_L \end{pmatrix}^T \tag{2}$$

where V is the air speed, ρ the air density, S the aircraft surface projected on the plane's vertical axis, S_y the aircraft surface projected on the lateral axis and C_D, C_Q and C_L are the aerodynamic force coefficients.

Medium to large aircraft usually have an Air Data System (ADS) and an Inertial Reference System (IRS). The ADS measures air data information, including V, ρ, α and β. The IRS measures angular position with regard to the earth and accelerations, including J_x, J_y and J_z. The aircraft's mass m is known from the takeoff mass and the used fuel. By substituting D, Q and L into (1) using (2), equations are obtained for which the only unknown terms are T, SC_D, S_yC_Q and SC_L. These terms are approximated by 4 multi layer perceptron (MLP), respectively $f_{T,\theta}$, $f_{D,\theta}$, $f_{Q,\theta}$ and $f_{L,\theta}$. MLP are deep learning models consisting of a succession of parameterized linear operations and non linear activation function. The parameters are optimized through gradient based optimizer, in order to minimize a loss function. They are known to be universal function approximators [9]. The loss function optimized in this model is given by (3).

$$\begin{aligned} L(\mathbf{X},\theta) =& [f_{T,\theta}(\mathbf{X}_T)\cos\xi + \frac{1}{2}\rho V^2(-f_{D,\theta}(\mathbf{X}_D)\cos\alpha\cos\beta - f_{Q,\theta}(\mathbf{X}_Q)\cos\alpha\sin\beta + f_{L,\theta}(\mathbf{X}_L)\sin\alpha) - mJ_x]^2 \\ &+ [\frac{1}{2}\rho V^2(f_{D,\theta}(\mathbf{X}_D)\sin\beta - f_{Q,\theta}(\mathbf{X}_Q)\cos\beta) - mJ_y]^2 \\ &+ [-f_{T,\theta}(\mathbf{X}_T)\sin\xi + \frac{1}{2}\rho V^2(-f_{D,\theta}(\mathbf{X}_D)\sin\alpha\cos\beta - f_{Q,\theta}(\mathbf{X}_Q)\sin\alpha\sin\beta + f_{L,\theta}(\mathbf{X}_L)\cos\alpha) - mJ_z]^2 \end{aligned} \tag{3}$$

This equation yields a loss function that aims to minimize the difference of the two terms in (1). θ represents the MLP parameters. $\mathbf{X}_T$, $\mathbf{X}_D$, $\mathbf{X}_Q$ and $\mathbf{X}_L$ represent the set of variables that have influence on respectively T, C_D, C_Q and C_L. For instance, $\mathbf{X}_L$ includes angle of attack, Mach number and aircraft configuration. X represents the set of all variables.

The key idea behind this model is that the error on equation (1) will increase during turbulence. The wind speed with regard to the earth is no longer identical at all points on the aircraft during turbulence, which means that airspeed and incidence angles represented by unique variables introduce errors in the equation.

Turbulence is therefore identified when the difference between the two terms of (1) is above a threshold.

3 Datasets

A commercial aircraft flight database was used to train and test a first model. These data, obtained from test flights, incorporate turbulence annotations by experts. As this data comes from real flights, turbulence annotations cannot be perfect. Additionally, strain gauges installed on the aircraft are used for model evaluation.

In order to validate the proposed approach, a synthetic flight dataset has be developed in this work. The flight dynamics data are generated using the aircraft simulator, developed by Stengel [8]. The control of the plane was made by decoupling the control over speed, heading and altitude. Realistic flight plans were made using a public dataset of French Falcon 20 environmental research aircraft of Safire [10]. Turbulence were added on 2% of the data using a Von Karman spectral density. Turbulence has been generated to meet the standards in MIL-HDBK-1797 [11].

The synthetic dataset allows us to check the relevance of the aerodynamic coefficients and the thrust values generated by the model, as these data are generated during simulation. The outputs of the MLPs $f_{D,\theta}$, $f_{Q,\theta}$ and $f_{L,\theta}$ do not directly represent the aerodynamic coefficients but $S \times C_D$, $S_y \times C_Q$ and $S \times C_L$. The outputs of the MLPs have therefore to be rescaled before the comparison.

Turbulence is added in a controlled manner in the synthetic dataset, which gives a perfect annotation of turbulence presence. This makes it possible to compute the performance of the turbulence detection with classical anomaly detection evaluation methods.

The performance assessment cannot be carried out in the same way on the real flight data, since turbulence annotations are subjective to expert knowledge on these data. It is crucial to be able to evaluate the turbulence detection method objectively and to be able to compare it to the original annotation. To this end, turbulence detected with the proposed model is not directly compared to the original annotation. A metric using the strain gauges is instead created, with the idea that a relevant turbulence detection method is one that detects instants at which the aircraft deforms significantly. The expression of this score is given by (4).

$$\mathrm{SCORE} = \frac{\sum_{i \in \text{gauges}} \underset{t \in \text{turbulence}}{\mathrm{VAR}} (g_i(t))}{\sum_{i \in \text{gauges}} \underset{t \in \text{overall}}{\mathrm{VAR}} (g_i(t))} \tag{4}$$

VAR stands here for the variance. Only the sensors most sensitive to turbulence are used to calculate this score, in order to obtain a more interpretable metric.

4 Conclusion

An hybrid model is proposed to detect turbulence in an unsupervised manner. Multi Layer Perceptrons are incorporated in the dynamic equation of the aircraft in order to compute missing terms. Since turbulence is a source of error in the dynamic equation, the model designates as turbulence the instants at which this error is highest. The model is evaluated on both a synthetic dataset and a dataset composed of flight data from a test aircraft. The synthetic dataset is used to check whether the missing terms in the equation have been correctly reconstructed by the model. Both synthetic and real data are used to evaluate the models ability to recover turbulence.

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