Anomaly Detection for Reaction Wheel Assemblies in Satellites

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In the recent decades, the number of orbital launches has increased consistently, leading to an exponential increase in the number of satellites orbiting Earth [1]. Once in orbit, satellites are expected to operate reliably for a long period of time (usually no less than 10 years) for their launch cost to be financially sound. Maintaining a satellite in good operating conditions requires keeping good track of its condition, which has been made unfeasible due to their large population. For this reason, automatic methods for analysis has been developed in the last years, with varying degrees of success [2], [3].

Among all components that must be kept in track, this project focuses on Reaction Wheel Assemblies (RWA), rotating discs that satellites use to alter their attitude by exploiting conservation of angular momentum. The nature of the operations of this component, in constant movement, makes it specially prone to failure. In particular, the point of contact between the rotating disc and the fixed axis (the bearing) has been home to a number of catastrophic errors in the past. Although such errors usually take place suddenly, past experience has shown that they are possible to predict by detecting abnormal behaviour in the friction torque at the bearing [4].

The purpose of this project, then, is to develop an algorithm that analyzes the sensor measurements coming from the RWA (in particular, the spin rate and the friction torque) and uses it to determine the condition of the component. Such algorithm is developed and calibrated using two sources of knowledge: a dataset with measurements on (simulated) RWAs whose condition is known, and information on the mechanisms of the RWA.

We first model the RWA as a friction system (that is, a relation between spin rate and friction) with a dry and a viscous component. While the viscous coefficient remains constant, the dry one is a combination of several different phenomena inside the bearings of the RWA, which we call subsystems. These subsystems are modelled in a similar way to Markov chains, with a discrete number of states. Each state has a friction and a residence time probability function associated, which determine what friction the subsystem produces and how long it takes until the next change of state. The friction, in particular, is affected by the condition of the RWA, and its distribution is fundamental to determine it.

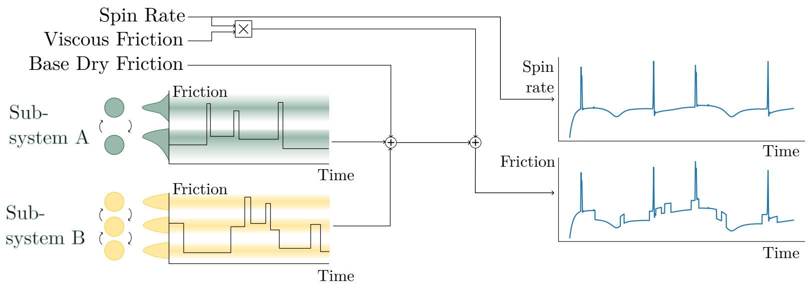

Figure 1: *model of the RWA.*

The algorithm developed runs in 3 stages. The first stage is the **changepoint detection**, in which the algorithm determines at what moments the friction torque in the RWA has changed abruptly. To do it, we exploit the linear relation between spin rate and friction by testing in windows of time how well a linear regression fits the relation between these 2 variables. When the squared error of the regression is above a certain threshold, a changepoint mark is raised at that point.

The second stage is the **changepoint assignation**, where the changepoints detected in the previous stage are distributed among the different subsystems that could have caused them. For this stage, we take advantage of the fact that the different subsystems produce jumps at different rates. To determine the allocation of changepoints that better fits the expected times of the different subsystems, a dynamic programming algorithm was used. The algorithm was also extended with the capability to ignore changepoints that do not fit the expected times, as they can be false positives produced in the previous stage.

The last stage is the **anomaly classification**, taking the strenght of the friction changes of each subsystems and using them to determine the anomaly present in the RWA. To accomplish this objective, histograms with the value of the friction are produced for each subsystem, and compared with the histograms obtained in the datasets provided. This is done using a simple neural network trained with the dataset.

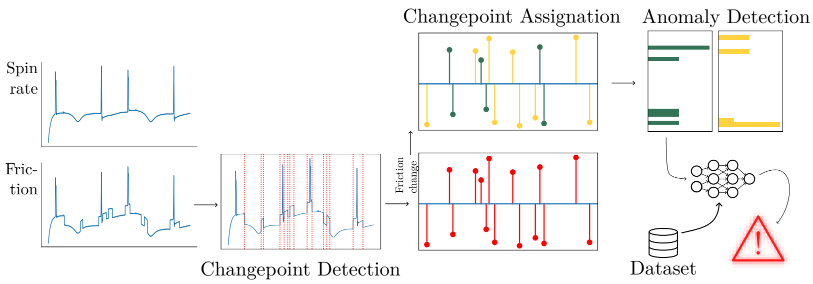

Figure 2: *anomaly detection algorithm.*

The algorithm was tested on both the data provided by an aerospace company and in synthetic data, with a good level of accuracy in both cases. For the datasets provided by the company, a total of 14 possible anomalies were considered. The algorithm achieved a sensitivity of 95-99% was achieved for most of the anomalies considered in the problems, with values around 85% obtained for the most challenging cases. Out of the 16 metrics proposed as Key Performance Indicators, 14 were achieved succesfully, with the remaining 2 being a 3% below the objective.

Bibliography

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