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Automated Fault-Detection for Small Satellite Pointing Control Systems using One-Sided Learning

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INTRODUCTION

As the size and prevalence of small satellite constellations grow, so does the interest in Prognostic and Health Management (PHM). In keeping with the small-satellite philosophy to maintain low design, manufacturing and operating costs, the small-satellite community is interested in efficient ground operations and fault management that does not require excessive labor from trained space systems experts [1]. The expanding scale of small-satellite constellations has posed a significant challenge for ground operations: how to find a sustainable way to monitor and manage a large amount of satellites efficiently with minimal cost?

To overcome this challenge, this research introduces an autonomous, ground-based fault-detection system that was trained using only nominal data, without requiring any prior expert knowledge of the spacecraft systems. By observing nominal data during the commissioning phase of the satellite, the fault-detection algorithm learned how to differentiate normal data from abnormal data without a labelled set of abnormal data. Training and testing results are presented to show how this one-sided learning method of fault-detection could detect un-trained failures related to reaction wheel performance. Specifically, this research demonstrates the utility of one-sided learning methods by autonomously detecting faults in reaction wheel bearing friction and wheel speed measurement, without any prior exposure to the failures.

METHODOLOGY

The development of the automated fault-detection system started from model simulation of an attitude control system for a small satellite. Following the training process, a normal dataset was generated and collected from the simulated attitude control system. With the collected dataset, the OC-SVM method was implemented for training.

Model simulation

An attitude control system for a small satellite was created from a closed-loop feedback system using MATLAB / Simulink. Figure 1 shows a design concept of a closed-loop attitude dynamics control system. A similar closed-loop feedback system was designed for reaction wheels where the commanded torque from the satellite was the input signal to the reaction wheel system (in Figure 2). The outputs from the reaction wheel dynamics system were reaction wheel momentum, torque, current, and angular velocity.

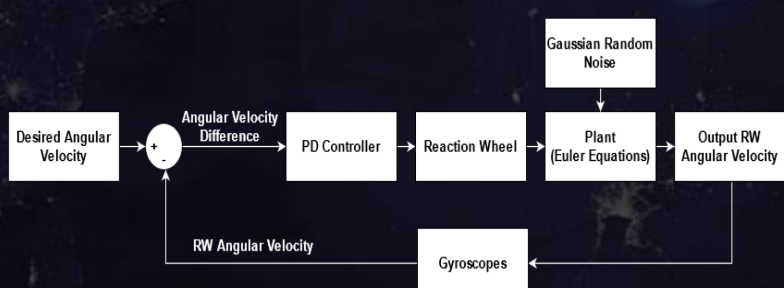


Figure 1: Attitude Dynamics Control System for a Spacecraft [2]

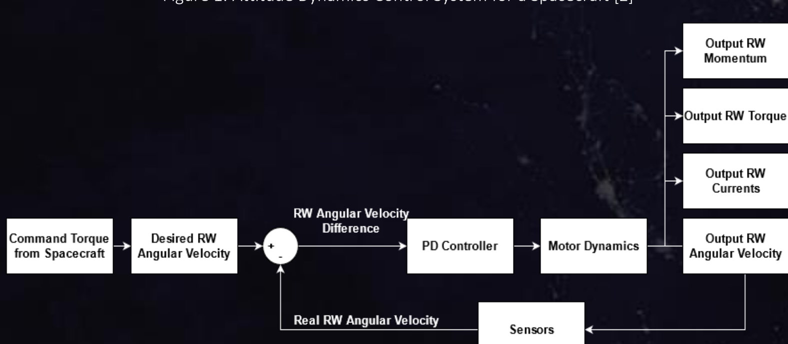
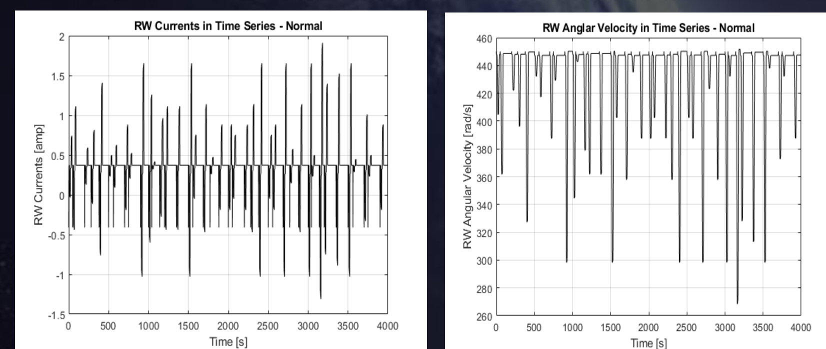


Figure 2: Reaction Wheel Dynamics [2]

The reaction wheel current and angular velocity were selected as the training features over the other outputs from the reaction wheel dynamics due to their mutual independence. The outputs of the desired slew rates with reaction wheel current and angular velocity in 4000 seconds are shown in Figure 3.



a) b)

Figure 3: Normal Slews in 4000 Seconds: a) Reaction Wheel Currents, b) Reaction Wheel Angular Velocities

One-Class Support Vector Machine

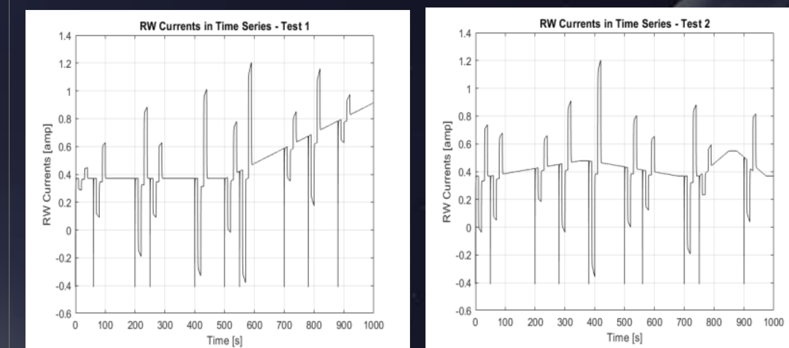
The OC-SVM methodology is from [3]. The principle of using this method is that labels or data responses are not required for training. Therefore, the training process only included normal behavioral attitude control system data. As reaction wheel current and angular velocity were selected as the training features, 10 consecutive data points were collected for reaction wheel current and angular velocity at each time point, to enable the algorithm to deduce relevant time-series features. Hence, there were 4000 data points collected for training with a data rate of 10Hz, and each training data contained 10 consecutive data points of reaction wheel currents and angular velocities. With the collected data, the system was trained to learn a hyperplane to separate normal behavioral data points with untrained abnormal behavioral data points. The input training data was firstly mapped into a Kernel function, then the general function of the separable hyperplane to determine the behavioral labels of the satellite was generated. After learning the decision function of the hyperplane, the detection system was able to identify failures. Label 0 is assigned to all normal data which is inside of the hyperplane and label 1 is assigned to all abnormal data which is outside of the hyperplane. Key functions are:

- Training Dataset: $X = \{(\boldsymbol{i(t)}, \boldsymbol{\omega(t)})\}$
- Mapping Function (Kernel): $K(\boldsymbol{X}, \boldsymbol{X'}) = \Phi(\boldsymbol{X})\,\Phi(\boldsymbol{X'})$
- Separable Hyperplane Function: $\boldsymbol{F(X)} = sgn((\boldsymbol{w} \cdot \boldsymbol{\Phi(X)}) - \boldsymbol{\rho})$
- Failure Detection: $y = \begin{cases} 0, & f(x_{test}) \geq 0 \\ 1, & f(x_{test}) < 0 \end{cases}$

Where, $\boldsymbol{x_{test}}$ is test dataset. When $f(x_{test}) \geq 0$, it represents that the test datapoint falls inside of the defined decision hyperplane. When $f(x_{test}) < 0$ it represents that the test datapoint falls outside of the defined decision hyperplane.

TESTS AND RESULTS

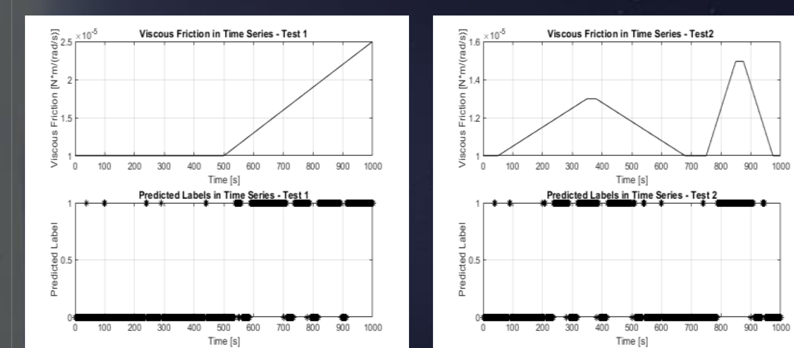
Two 1000-second tests were performed for the trained detection system. Huang et. al [2] provided an outline for the tests. Each test contained ten random slews with simulated bearing degradation failures. In the first test, friction failures were added at the 500th second of the simulation. At the 500th second, the friction failure occurred and began to increase gradually with time. For the second test, friction failures were added in two different phases of the simulation following trapezoidal-like viscous friction profiles. The purpose of performing these two tests was to examine the detection capability of the trained system on long-term failures and intermittent failures in the attitude control system. Figure 4 shows the plots for the two test datasets (the same test data was used in [2], but for a different fault detection methodology).



a) b)

Figure 4: a) Test 1 Dataset - Reaction Wheel Current , b) Test 2 Dataset - Reaction Wheel Current [2]

The tests were then performed using LIBSVM ([3], [4]). The behavioral labels for the two tests were predicted. The predicted results are presented in Figure 5. Comparing the results from the two tests, the proposed one-sided learning-based detection system showed good performance on test 1, where the detection accuracy reached approximately 90%. However, the system showed a lower detection accuracy on test 2 where the detection accuracy was around 60%.



a) b)

Figure 5: Prediction Results for Tests: a). Viscous Friction Vs. Predicted Behavioral Labels for Test 1, b). Viscous Friction Vs. Predicted Behavioral Labels for Test 2

From the results, this one-sided learning-based detection system performed better when detecting normal data as compared to detecting anomalies. Future research will put effort into developing different fault-detection systems by implementing other suitable one-sided learning algorithms.

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