Anomaly Detection in a Multi-engine Aircraft

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Abstract. This paper describes an anomaly detection algorithm by monitoring the spin-down of jet engines. The speed profile from multiple engines in an aircraft is cast as a singular value monitoring problem. This relatively simple algorithm is an excellent example of onboard, lightweight feature extractor, the results of which can feed more elaborate trouble shooting procedures. The effectiveness of the algorithm is demonstrated using aircraft data from one of Honeywell's airline customers.

1 Introduction

Monitoring jet engines is a topic of growing interest among engine makers, aircraft manufacturers and airline operators [1]. Architecture that addresses the fault diagnostic problem using a combination of onboard pre-processors and off-board reasoners is gaining considerable attention [2]. Within this architecture, onboard algorithms process large amount of frequently available data to retain key features. These relatively small features or anomalies are then analyzed by ground-based reasoning systems. In this paper, we describe one such anomaly detection for analyzing the spin-down speed profile of a jet engine.

At the end of the flight, the pilot issues a shutoff command. In response the engine controller starts to reduce fuel to individual engines. At some point during this shutdown, fuel is completely cut out and the engine spins down on its own inertia. This is called the spin-down phase. By monitoring aberration of the speed profile during spin-down, one can detect anomalies for incipient engine faults that cause abnormal drag. Basic principle, algorithm design, and results on one of Honeywell's airline customer are discussed in this paper.

2 Basic Principle

The rate at which engine speed decreases during the spin-down phase is governed by the frictional losses at the bearing and the parasitic drags imposed by the gear-box. Let N_i denote the core speed of the ith engine. A simple torque balance gives:

$$J_i \frac{d\ (2\pi N_i/60)}{dt} = -k_i^{par}(2\pi N_i/60) \tag{1}$$

where J_i is the moment of inertia of the core shaft, k_i^{par} is the frictional loss coefficient. Integrating equation (1) will generate the spin-down profile. Define a

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time origin t_i^0 for the ith engine such that $N_i(t) = \mathcal{N}$, where $\mathcal{N}$ is a pre-defined constant. Now we start observing the engine spin-down for T time interval starting from t_i^0. Re-arranging and integrating (1) we get:

$$N_i(t) = \mathcal{N}\ \mathrm{e}^{-(k_i^{par}/J_i)t}, \quad t_i^0 \leq t \leq T + t_i^0 \tag{2}$$

Define τ_i as the closed set $[t_i^0, T + t_i^0]$. We shall use the short hand notation $N_i(t), t \in \tau_i$ to describe equation (2).

On the regional jets (RJ) operated by a Honeywell's customer we have 4 interchangeable engines. From the interchangeability property of the engines, it follows that moment of inertia J_i will be *almost* identical to each other. Similarly frictional losses characterized by k_i^{par} will also be close to each other. In other words, the interchangeability property implies:

$$k_i^{par} \approx k_j^{par} \text{ and } J_i \approx J_k, \quad i, j = 1, 2, 3, 4 \tag{3}$$

$$\text{and hence } \{N_i(t), t \in \tau_i\} \approx \{N_j(t), t \in \tau_j\} \quad i, j = 1, 2, 3, 4 \tag{4}$$

That is, the spin-down profile of all four engines should evolve *almost* identically over a pre-defined time. Note that the length of this time interval is identical, but $t_i^0 \neq t_j^0; i, j = 1, 2, 3, 4$. In the next section, we will design an anomaly detection algorithm based on this principle.

3 Algorithm Design

One of the widely used algorithms for fault diagnosis, given a nominal model is parameter estimation. Stated simply, such model-based fault diagnosis algorithms estimate the model parameters using actual observations. Deviations from design values are indicative of incipient faults[3,4]. In this paper, we investigated a much simpler approach, based on singular values. For the ith engine, starting from t_i^0 we sample the engine speeds N_i at a uniform rate. Let T time interval contain m samples. Define an $m \times 4$ observation matrix X as follows:

$$X = [\boldsymbol{x}_1\ \boldsymbol{x}_2\ \boldsymbol{x}_3\ \boldsymbol{x}_4]; \text{ where } \boldsymbol{x}_i = [N_i(1)\ N_i(2)\ \ldots\ N_i(m)]^T \tag{5}$$

It follows from (4) that the matrix X has only one independent row. Hence the rank of this matrix will be very close to 1. That is, $\mathrm{rank}(X) \approx 1$. A computational tractable way of calculating the rank of a matrix is using singular value decomposition (SVD) of the covariance matrix, $\mathrm{cov}(X)$. Since $\mathrm{rank}(X) \approx 1$ the singular values of the covariance matrix satisfy the following property:

$$\sigma_1 > 0, (\sigma_2, \sigma_3, \sigma_4) \approx 0, \quad \text{where } \sigma_1, \sigma_2, \sigma_3, \sigma_4 = \mathrm{SVD}(X^T X/(m-1))$$

From the property of SVD, we have $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \sigma_4 \geq 0$. Hence, closeness of σ_2 to zero is sufficient to monitor the rank of the covariance matrix. By monitoring σ_2, the algorithm compares the spin-down profile of engine i with engine $j, \forall i, \forall j, j \neq i$. The spin-down equation ((2)) does not enter the algorithm

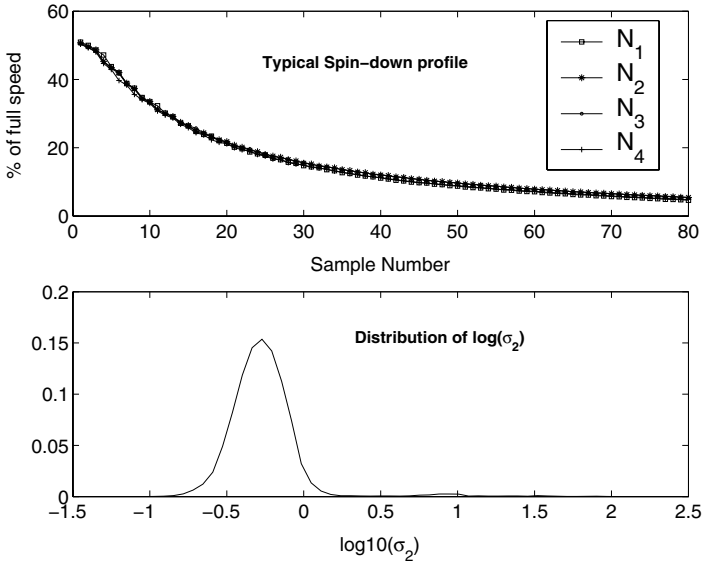

Fig. 1. Data used for algorithm design

explicitly. However, the insight provided by the model is used in designing the detection algorithm. Large deviations in the spin-down profile of engine i indicated by larger value of σ_2 is an indication of possible incipient fault. In real life small perturbations will be introduced as a result of sensor noise and typical engine-to-engine variation. Although internal conditions within the engine core remain constant, external factors like wind speed and engine position cause perturbations in the spin-down profile. Thus one needs to threshold σ_2 to suppress such effects.

Historical data from airline A spanning 10672 flights from 31 aircrafts was used to design the detection threshold. Within this data set, there were no reports of major engine failures. Based on conversations with engine experts, $\mathcal{N}$ was set at 50% of full speed. m was fixed at 80 samples, primarily constrained by on-board memory availability. Frequency of data collection was fixed by existing data collection system. A typical spin-down profile is shown in the top subplot in Fig. 1. The speed decay profiles from the four engines are *similar*, but not identical. Bottom subplot in Fig. 1 shows distribution of $\log(\sigma_2)$ from all 31 aircrafts[1]. Based on this distribution, we identified threshold θ such that the probability $P(\log(\sigma_2) > \theta) < 0.001$. We imposed an additional condition to eliminate outliers and look for sustained excursions in σ_2. If 5 successive values of $\log(\sigma_2)$ exceed 0.6, we declare an anomaly and Transmit $N_i(t)$ to the ground station for further analysis. Results of applying this algorithm on test aircrafts is discussed in the next section.

[1] Since the covariance matrix is symmetric, all the singular values are positive.

4 Results and Conclusions

The algorithm described in the previous section was tested on data collected from airline A. Figure 2 shows the trace of $\log(\sigma_2)$ from two engines over this test period. Aircraft 501 has some outliers, whereas aircraft 505 has sustained excursions. Small variations between two engines spin-down cause these outliers. At this point, it is believed that there may be a small influence of wind direction. Although, an interesting hypothesis, we were more interested in sustained variations caused by inherent malfunction within an engine. Possible engine anomaly in aircraft 505 is clearly identified by a jump in the σ_2.

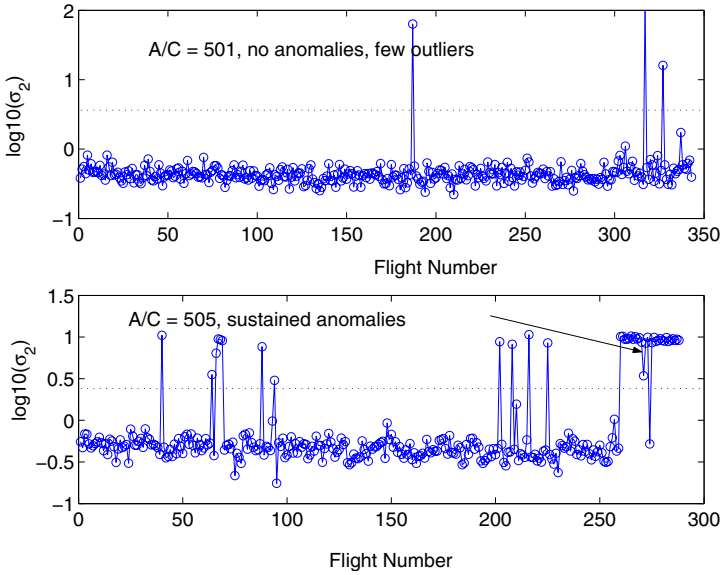

Fig. 2. σ_2 trace on test aircraft data

The trace of $N_i(t)$ for these sustained excursions is shown in Figure 3. Subplots left to right in Figure 3 indicate 8 consecutive flights. It is clear from the N_i trace that N_3 or engine #3 is spinning down rapidly and towards the end it comes to a grinding halt. This anomaly persisted for 16 consecutive flights after which this engine was removed for further trouble shooting. The anomaly clearly localized the problem to the bearing and the gearbox section of the engine. Further analysis at the repair shop revealed a malfunctioning oil pump. Malfunctioning oil pump imposes abnormal parasitic drag on the engine shaft and this gets pronounced as the engine spins down. At 100% speed, this parasitic drag gets masked by the turbine and the compressor. Historically, such incipient faults have gone un-noticed until secondary effects like high oil temperatures cause preventive shutdown. In this respect, the algorithm was successful in achieving what we had designed it for—anomaly detection for engine health monitoring.

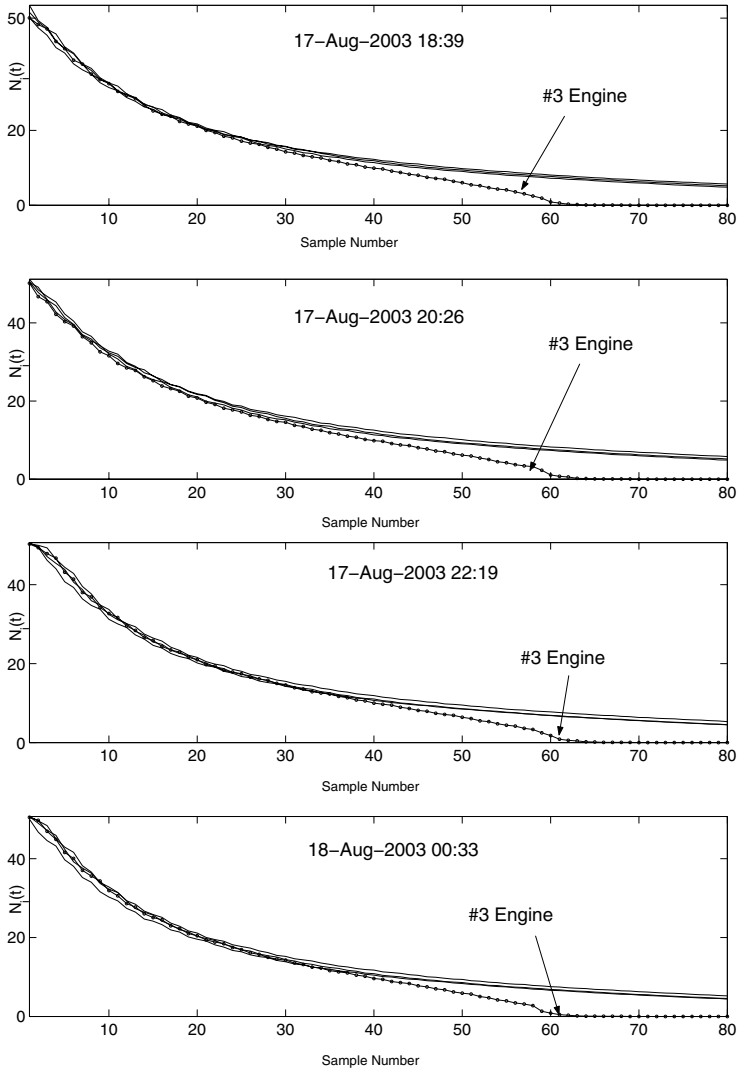

Fig. 3. N_1-square, N_2-star, N_3-circle, N_4-plus. Engine at position 3 (indicated by an arrow) in aircraft 505 is markedly different. There is a strong indication of abnormal drag on the shaft.

The algorithm described in this paper is a good example of how principles of linear algebra, statistics together with engineering knowledge can be used to design simple on-board anomaly detectors. To date, the algorithm has triggered anomalies in two aircrafts (A/C 505, 509), both with confirmed oil module malfunctions.

Future enhancements to this algorithm include analyzing the sample number at which an engine comes to a screeching halt. This abrupt trend is shown by the trace of $N_3(t)$ in Figure 3, which hits a zero value at about 60th sample. It is generally believed among repair engineers that this information can be used to isolate forward and rear bearing. We plan to embark on such investigations in the future.

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