Random model of vibrations for Foreign Object Damage detection in a civil aircraft engine

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Abstract

In this article we analyze several vibration time series measured on a real fan test rig before and after it is hit by a flying object. We show first evidence that a windowed autoregressive model may be used to detect the shock after it occurred. We compare these results with a second time series that measures the rotation period of the fan. Lastly we repeat this experiment using adaptive autoregressive estimation instead of the classical AR estimation algorithm. First results show that vibration data allow better prediction. Furthermore, the windowed AR estimation algorithm seems to perform better than the adaptive one.

1 Introduction

Foreign Object Damage (FOD) is a serious threat to civil aicraft engines, all the more given that it occurs and vanishes very quickly. One can detect FODs with the help of vibration sensors because they elicit a short and intense rise in vibration amplitude, as shown by Fig. 2 (top). However, for several reasons this burst may be hard to detect online, or may trigger false alarms when buried in real engine noise.

In this article we consider detecting FODs even after the shock, by monitoring vibrations sensors and the duration of each shaft revolution, and modeling them as random signals. This approach is commonplace in structural health monitoring [1] but to the best of our knowledge was not applied so far to FOD detection.

1

2   Methods

The test system is not a complete aircraft engine, but a partial fan with a small number of blades used by Snecma for testing, as depicted by Fig.1. The shaft angular position can be computed thanks to a keyphasor that emits a pulse at the end of each cycle, and whose raw output is noted $tacho(n)$. Furthermore, the amplitude of vibration is measured with a accelerometer mounted on the test rig, and that outputs $vib(n)$. At a specific time instant, a cannon fires a projectile at a controlled speed, aimed at a precise blade.
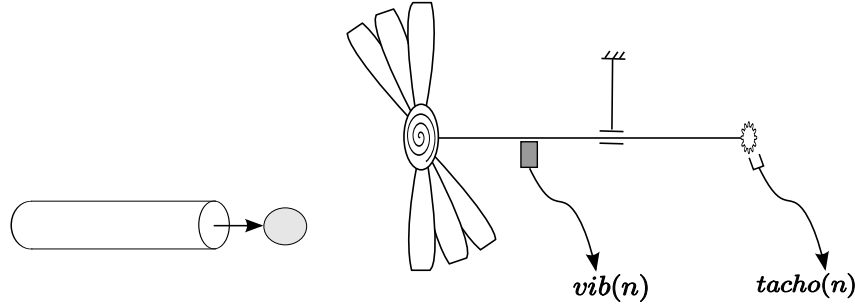

Figure 1: Test rig composed of a single fan with a small number of symmetric blades, and equipped with a tachometer and a vibration sensor.

The available data are provided by the Health Monitoring Department of Snecma. It includes vibrations and raw keyphasor for three different experiments, sampled at 25000 Hz, during several hundred seconds. Raw vibration data is kept almost unchanged, since it shows no trend, variance fluctuation nor slow periodic variation. Because our aim is to detect the shock after its occurrence, we remove the short time interval that corresponds to this event, represented by Fig. 2 (top). The beginning of the shock is found by thresholding the amplitude with a fixed arbitrary threshold, the length of the event is set to 2s.

Meanwhile, raw keyphasor data is preprocessed with a local polynomial interpolation and simple root-finding so as to get precise zero-crossing time, and hence the duration of successive periods, given in seconds. The result is shown by Fig. 2 (bottom), where the shock is easily seen. In a similar way, we remove the time interval where the shock occurs. Moreover, we detrend and deseasonalize the data, to get rid of a periodic modulation of the signal.
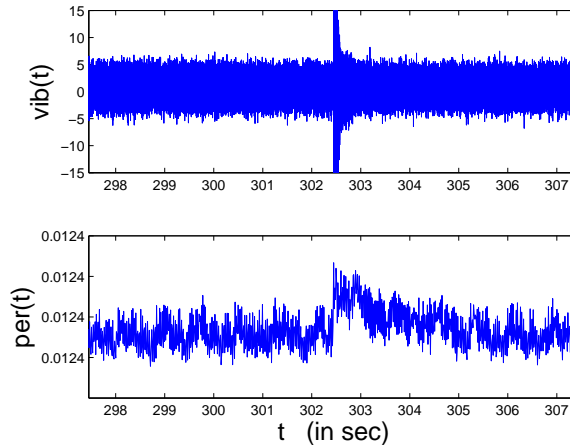

Figure 2: Time series of (top) vibration sensors $vib(t)$ and (bottom) period duration.

The obtained time series are modeled as autoregressive (AR) stationary processes, whose coefficients are estimated by two algorithms. First we use the classical Burg algorithm [2] with nonover-

lapping windows, then we we run an adaptive autoregressive algorithm [3]. Dimension reduction is simply performed by PCA.

3   Results

We first present results relative to windowed AR estimation and projection, in the case of vibrations. Each vibration time series is divided into 5 blocks of equal length. The first four blocks correspond to pre-shock data, the last block to post-shock data. The order of AR models is set to 10, after a first model selection step that is not discussed here. The dimension of the reduced space obtained by PCA is set to 2. For each of the three separate FOD experiments, Fig. 3 shows the resulting scatter plot. Pre-shock (resp. post-shock) dots are in blue (resp. red). In all three cases, post-shock data are represented by an isolated point. However, in cases 1 and 3 there is another distant point, whose presence is unexplained so far.
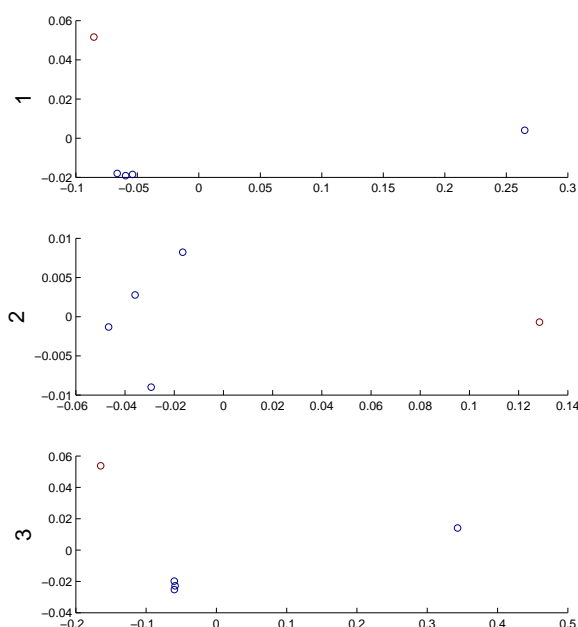

Figure 3: Scatter plot of AR coefficients projected in a bidimensionnal reduced space, for the three successive vibration data blocks. The last point -in red- corresponds to the post-shock part of the time-series.

Now we compute adaptive autoregressive coefficients [4], and project them in 3-dimensional space. We discard the beginning of the obtained time series to get rid of convergence transient, and plot the three trajectories in Fig.4. The green part of the curve stands for the post-shock time interval. In cases 1 and 3 we notice a sudden change in the direction of the tangent to the curve. This lack of frank discontinuity may result from the very nature of the adaptive algorithm, which uses past data to overcome the underdetermination of the estimation problem.

Lastly we have made the same experiment with the time series $per(t)$, but must conclude that so far no interesting result was found. Our first intuition was that the aftershock could last longer with the period duration, but it turns out that the order of magnitude is roughly the same, as evidenced by Fig. 2.
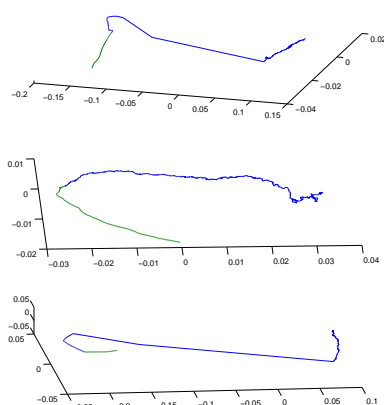
3

Figure 4: Trajectory plots of adaptive AR coefficients projected in a 3-dimensional reduced space, for the three successive vibration data blocks. The last part -in green- corresponds to the post-shock part of the time-series.

4   Conclusions and future work

In this article we tackled the issue of detecting an FOD after the shock has occured. We have presented preliminary results obtained with a test rig that is different from a real aircraft engine. However some evidence is shown that elementary filtering and dimension reduction could be sufficient for such detection.

As more in-depth investigations are needed, we first plan to fine-tune the model selection and estimation of the autoregressive model coefficient. The process type is so far restrained to AR model, but may be extended to several classical processes (ARMA, ARIMA, . . .) as well as others more likely to be found in vibration and health monitoring litterature (TARMA, . . .). The order choice must be discussed in detail, as well as goodness-of-fit tests results. Similarly, the tradeoff between the window length and the number of available points will be debated on statistical grounds in order to balance the lack of data. Lastly, the physical justification for modelling normal vibrations with such AR process will be traced back in the relevant litterature[1]; then the mechanical effect of a FOD on this model will be derived, so as to explain the effect on the estimated AR coefficients.

In the much more complex case of a real engine, all the previous steps will be taken successively so as to decide whether or not FOD can be detected after their occurrence. We remarked already that vibrations have a much more harmonic content in that case than with the test rig, which could impose further constraints on the AR model.

References

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[2] P.J. Brockwell, R.A. Davis, (2002) Introduction to Time Series and Forecasting, second edition, Springer-Verlag, New York.

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[1] it is easy to see why an approximate solution of the deterministic differential equation $x'' = sin(\omega t)$ can be found in an AR form, by simply replacing x'' by its finite difference counterpart $x(t+1) - 2x(t) + x(t-1)$ and considering the sine as a random process.

4