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Change Detection for Improved Maintenance Notification and Remaining Useful Life Calculation

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Abstract

HUMS (Health and Usage Monitoring Systems) provide enhanced safety and availability by alerting maintenance personnel when components (shaft/gears/bearings) have degraded or become damaged. Proactive maintenance ensures that a degraded component will not fail in flight. Often, the damage is from high cycle fatigue or other relatively slow degradation processes. However, there are events, such as maintenance, that result in a step-change in the component's health. While high cycle fatigue degradation can be trended, a step-change in component health presents a challenge.

For example, HUMS data from recent maintenance on a Thompson coupling resulted in a large 3/rev increase in vibration, which caused a step-change in the coupling health. Trending tools, which are, in effect, low-pass filters, would not immediately alert maintenance or the crew to the anomaly. Thus, a process to detect the change in health is needed which is both sensitive to change and provides protection against false alarms.

Change detection in manufacturing process control has long been used for quality control. Several statistical tools have been developed to alert when the manufacturing status is out of specification. However, the research team is interested in determining when the high-cycle fatigue process is out of control. That is, when the difference between the component health trend, and measured component health, are statistically different enough, an alert should be sent to the maintainer, and the trend is reset to reflect the step-change.

This paper describes the development of a CUSUM (cumulative sum) statistic between a component health trend and the measured component health. This allows the automated capture of maintenance or other events that would result in a component step-change in health.

Keywords: CUSUM, Health indicator, Maintenance alert, RUL, Smith Chart.

Introduction

Health and Usage Monitoring Systems (HUMS) were able to provide the most benefits and safety gain in rotorcraft aviation. HUMS supports several functions that improve safety by proactively reporting the performance of the aircraft. Those functions may include notification of flight manual exceedance, flight data monitoring to support a safety management system, automated engine performance checks, drivetrain diagnostics, or rotor track and balance. Collectively, HUMS provides actionable information so that maintainers can make data-informed decisions (Ref 1).

Fatigue damage can occur due to tensile cyclic loading. The resulting fatigue crack growth was modeled by a power law (Ref 2). For this type of damage, the component health indicator (HI) was trended. Trending facilitates both a threshold (e.g., alerting) and an estimate of the remaining useful life (RUL). The HI and RUL were then used to provide alerts (e.g., actionable information) to the maintainer that a decision should be made about when to perform a corrective action. This trending and alerting capability, however, does not address a step-change in component health.

A step-change in component health occurs when some event, such as maintenance, results in degradation not associated with high cycle fatigue or an improvement due to maintenance. That is, the RUL modeled in Ref 2., does not adequately model events that are not associated with high cycle fatigue. This paper introduces a method of providing actional information for drivetrain diagnostics due to a step change in component health.

On rare occasions, maintenance may impair a nominal component. In this example, a Thompson coupling on the tail rotor driveshaft was damaged. As a result of maintenance, there is a large increase in the 3rd harmonic of the shaft. This is indicative of a coupling problem. The HUMS should alert the maintainer as soon as possible that corrective action is needed, as the continued operation of the component will result in lower reliability of the aircraft and potential loss of tail rotor authority.

In effect, a step-change is a case where the high cycle fatigue model is no longer in a state of “control”. That is, the measured HI diverges from the filtered HI trend. In approaching this as a statistical process control problem, there are powerful tools that have been developed to detect this type of event. In selecting a technique, it is important that it has a short average run length (ARL, the expected number of subgroups until a control chart first signals). For this reason, the cumulative sum (CUSUM Ref 3.) was used.

Analysis Chain Prior to Change Detection

The change detection event is the result of a chain of analysis: feature extraction, thresholding, and the failure of trend analysis. Condition indicators (CI) are analyses that return feature representative of the state of the component under analysis. Some CIs have physical meaning, such as the velocity of the shaft's first harmonic. Other CIs are statistical features of a signal, such as the RMS of the time synchronous average (TSA) of a shaft. CIs generally use signal processing techniques to improve the signal-to-noise of a feature. A good example of signal processing for CI development is given by Večeř (Ref 4).

Thresholding is needed to determine when a maintenance action is needed. There are a number of approaches that can be taken, but for this example, a health indicator (HI) paradigm was taken (Ref 5). As there are often many different failure modes of a component, no single CI can be used. Additionally, often there are little to no failure examples for a component, which limits the usefulness of deep learning or other AI-based techniques.

Given that there is almost always nominal data, the technique treats the CIs as distribution, such that the HI is a function of distributions. The success of this implication depends on the validity of the input assumptions. That is, the performance of the HI is dependent on the CI distributions being known, identical, and independent. For this reason, a normalizing and whitening transformation is performed on 1 to *n* CIs. Cholesky decomposition is performed on the *n* CIs inversion covariance:

$$\boldsymbol{LL}^{*} = \boldsymbol{\Sigma}^{-1} \tag{1}$$

This whitening/normalizing transformation is applied to the CIs as:

$$\boldsymbol{Y} = \boldsymbol{CI} \times \boldsymbol{L} \tag{2}$$

The HI algorithm is then:

$$HI = {}^{0.35}/_{crit}\sqrt{\boldsymbol{Y}^T\boldsymbol{Y}} \tag{3}$$

The HI can be scaled between, say 0 and a maintenance warning of 0.75 and a maintenance alarm of 1.0. The critical value (*crit*) is set by the inverse cumulative distribution function of the HI for a probability of false alarm (PFA) at 0.35. That is, if the PFA of the HI in (3) is 1e-6 at 0.35, then one is rejecting the hypothesis that the component is nominal at that level. The maintenance paradigm then suggests that there is a high degree of assurance that the component is no longer good (e.g. its damage) as an HI of 1.

Trending and RUL Estimation

Component degradation modeling assumes a high cycle fatigue process. This is a broad topic [2], but many models assume that material crack length can be expressed as a power law function of the load, current crack length, and the rate of change in the crack length. If one assumes that the HI is proportional to damage (e.g., crack length), then one such estimate for the RUL is:

$$RUL = \frac{dt}{dHI} \times HI \times \log(HI) \tag{4}$$

This only requires the implementation of a state observer (such as a Kalman filter) to estimate the HI and derivative of the HI, dHI/dt (see [6]).

The CUSUM for Change Detection

The CUSUM is a sequential method for detecting a change in mean value. The average run length, that is, the ability to detect a change, is better than Shewart control chart when the shift is less than two standard deviations. The deviation from the mean is from the trend which models high cycle fatigue. In that way, changes to do a maintenance event, or catastrophic event, will deviate from the HI trend and will be detected by the CUSUM.

The CUSUM is a type of detection problem defined by:

- α: the PFA, e.g., stating a change occurred when in fact it did not,
- β: the probability of not detecting a change when it fact, it did occur, and
- δ: the amount of shift in the process that one wishes to detect, as a multiple of the process standard deviation.

Note that α and β are calculated in terms of one sequential test, where one monitor, S_m, until there is either an out-of-control signal or the signal returns to its nominal value, the HI trend.

These values are used to define the decision parameter needed for the test. Because the change detection will be used for both a deviation high (something broke), and low (it was repaired), the following sequential values are calculated:

$$S_{hi}(i) = max(0, S_{hi}(i) + d_i - k) \tag{5}$$

and

$$S_{lo}(i) = max(0, S_{lo}(i) - k - d_i) \tag{6}$$

Where $S_{hi}(0)$ and $S_{lo}(0)$ are 0, and d_i is the difference between the trend and the unfiltered HI value at the time i. When either Where $S_{hi}(i)$ or $S_{lo}(i)$ exceeds a value h, the process detects a change, and a new trend is started. The values k and h, are defined as:

$$k = \frac{\delta \sigma_d}{2} \tag{7}$$

Where σ_d is the standard deviation of the difference between the trend and HI, and

$$h = 2k/\delta^2 ln \left(1 - \beta/_{\alpha}\right) \tag{8}$$

Examples: Thompson Couple Repair vs. Aux Bearing Replacement

An operator of a HUMS-equipped Bell 407GX performed standard maintenance on the oil cooler Thompson coupling. Approximately 30 hours after the maintenance was completed, the HUMS sent a warning alert (HI > 0.75). Viewing the CIs that were used in the HI (shaft order 1, shaft order 2, and shaft order 3), it was found that the shaft order 3 CI was in warning. Shaft order 3 is associated with in coupling assembly issue or coupling failure. An inspection of the coupling showed that it was assembled incorrectly. A repair was made, and the aircraft returned to service. The HI dropped to a nominal level. Figure 1 displays the current HI and trend during high shaft order 3 measurements and post-repair.

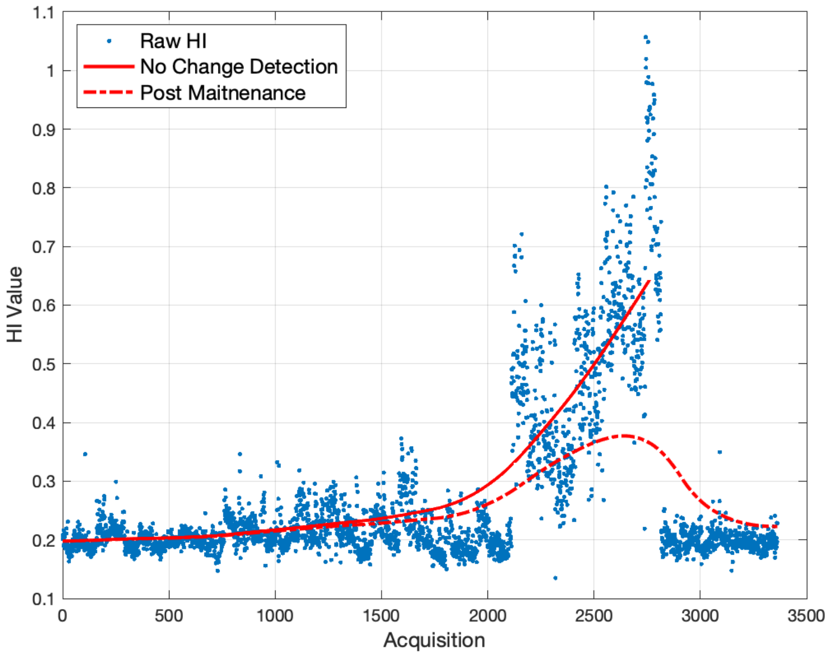

Figure 1 Thompson coupling fault, no change detection

Note that ideally, the jump in the HI due to maintenance would have automatically alerted the maintainer so that the inspection could be effectuated immediately. Similarly, once the repair was made, automated alerted that the repair worked would be a good feature.

In implementing the change detection algorithm, a δ = 2.5, β = 0.05, and α = 0.01 was set. The calculated σ_d = 0.11 gives a k of 0.13 and h of 0.19. The resulting change detection results are seen in Figure 2. The CUSUM change detection quickly alerts the change in HI due to maintenance. Figure 2 captures these step-change events and would better alert the maintainer that something of note had occurred.

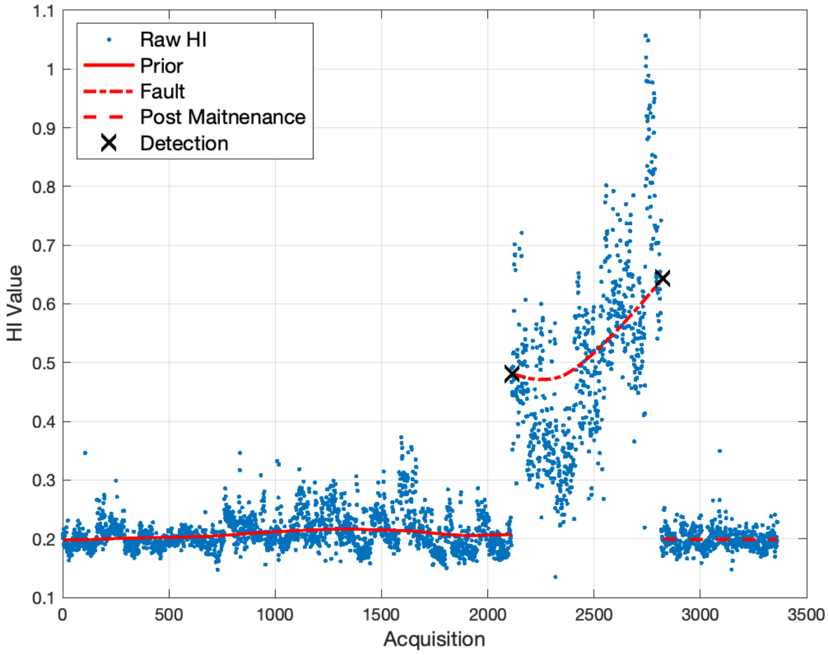

Figure 2 Change Detection based on CUSUM

In a second example, the HUMS recorded an inner race fault on the Aux duplex bearing (Figure 3). As this was a new gearbox, this could be explained by wear debris in the oil, so the decision was made to change the oil (x-axis index 2425). This did temporarily reduce the HI, but it seems the bearing was damaged, and an inner race fault propagated. The bearing was replaced at x-axis index 3312.

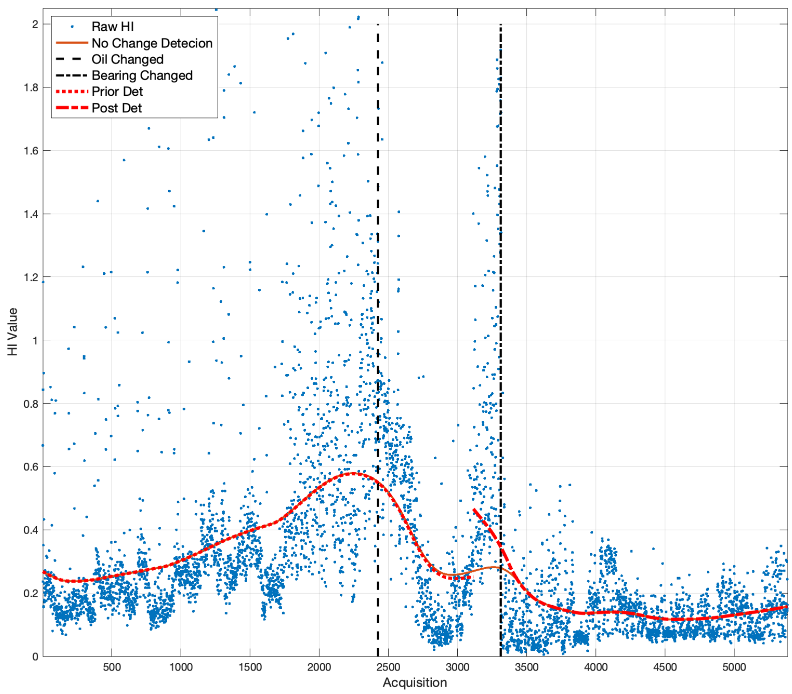

Figure 3 Change Detection on an Aux Bearing

This detection clearly did not capture the maintenance events. This is likely due to the much larger σ_d calculated as 0.25. One assumption that is violated is that the standard deviation of the HI is not stationary. That is, the standard deviation is a function of time. This suggests that for a generalized change detection algorithm, a more robust calculation of σ_d (time varying over some length of window) is needed or that techniques other than CUSUM may be more appropriate.

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