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A Constant False Alarm Rate- (CFAR) Based Change Detection Approach to Helicopter Diagnostics

by Kenneth Ranney, Hiralal Khatri, Jerry Silvious, Kwok Tom, and Romeo del Rosario

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14. ABSTRACT

We extend results obtained for fault detection and present a procedure for calculating condition indicators that is tailored to detect a recently observed fault. We illustrate how it arises naturally from consideration of statistics commonly calculated as part of constant false alarm rate (CFAR) target detection algorithms.

15. SUBJECT TERMS

Constant False Alarm Rate, Diagnostics, Fault Detection

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1. Introduction

The U.S. Army has recently invested substantial time and effort in developing a condition based maintenance (CBM) system for its helicopter fleet. This system detects nascent equipment faults before they can progress to catastrophic malfunctions that seriously increase aircraft downtime and reduce fleet readiness (*1*–*3*). Clearly, a completely effective CBM system could realize both time and cost savings and increase operator safety by indicating components that require replacement. This is especially true if a periodic inspection of the faulty component is not scheduled in the near future.

Part of the CBM system development consists of determining suitable condition indicators (CIs) capable of detecting incipient faults. These CIs then serve as input features to statistical analysis/detection algorithms that, in turn, decide if the feature level exceeds an alarm threshold. If the alarm threshold is exceeded, then the diagnosed fault is reported, and it can be repaired at the earliest opportunity.

The CI definitions are often formulated with the goal of detecting specific faults frequently encountered during an aircraft's maintenance cycle. Experimental investigations have also been conducted to better understand the physical phenomena and manifestations of various failure modes (*4*). The results have enabled investigators to better understand the underlying problem and define new CIs as the need arises. Hence, there is a need for continued formulation of additional CIs as new faults are discovered and new maintenance data becomes available—CIs that are uncorrelated with the existing ones.

The U.S. Army Research Laboratory (ARL) has also addressed the diagnostics problem, exploiting archived maintenance records collected by the Health and Usage Monitoring System (HUMS) installed on specific Apache helicopters. We have obtained failure dates and failure modes for these aircraft and examined the relevant sensor data. Based on this analysis, we have been able to formulate new definitions for CIs to detect the onset of the described failure modes. These definitionsare similar to the classical constant false alarm rate (CFAR) and change detection test statistic definitions so familiar to the radar community. This report describes our approach and presents experimental results obtained using HUMS data from several aircraft, the vast majority of which did not experience the failure mode targeted by the new CI.

2. Technical Approach

As mentioned in section 1, we had access to certain maintenance records from two specific Apache helicopters together with the failure modes that were discovered as a result of maintenance inspections. (This information was provided by Dr. Jonathan Keller, U.S. Army Aviation and Missile Research Development and Engineering Command (AMRDEC).) The available HUMS data comprised a set of preprocessed spectra collected at variably, sometimes widely, spaced intervals around the indicated failure dates. It included only a single example of a specific failure mode with a small amount of maintenance history available for each example. This sparseness of the data set exhibiting the failure mode of interest, together with the small number of available samples (both failed and non-failed) suggest that this investigation be considered as preliminary. Additional data examples (both failed and non-failed) are required to place it on a sound statistical footing. Still, the samples separated in time from those closest to the time of failure appear relatively consistent to one another in a sense that we quantify below. In addition, we observed certain unique qualities of the spectra collected closest to the failure date, and we developed CI definitions intended to detect these qualities if present.

2.1 Failure Mode and Description of Available Data

The failure mode that we initially investigated was due to the failure of the primary hydraulic pump on the left-hand side of the main transmission. To our knowledge, this particular failure mode instance was not detected by the current set of CIs, and it was identified during a manual inspection. In what follows, we will denote this as "fault 1". Spectral data records from the HUMS system were available for the aircraft as described in table 1; these data provided the basis for our development of a new CI definition.

Table 1. Data available for fault diagnosis for Aircraft Tail number 5180.

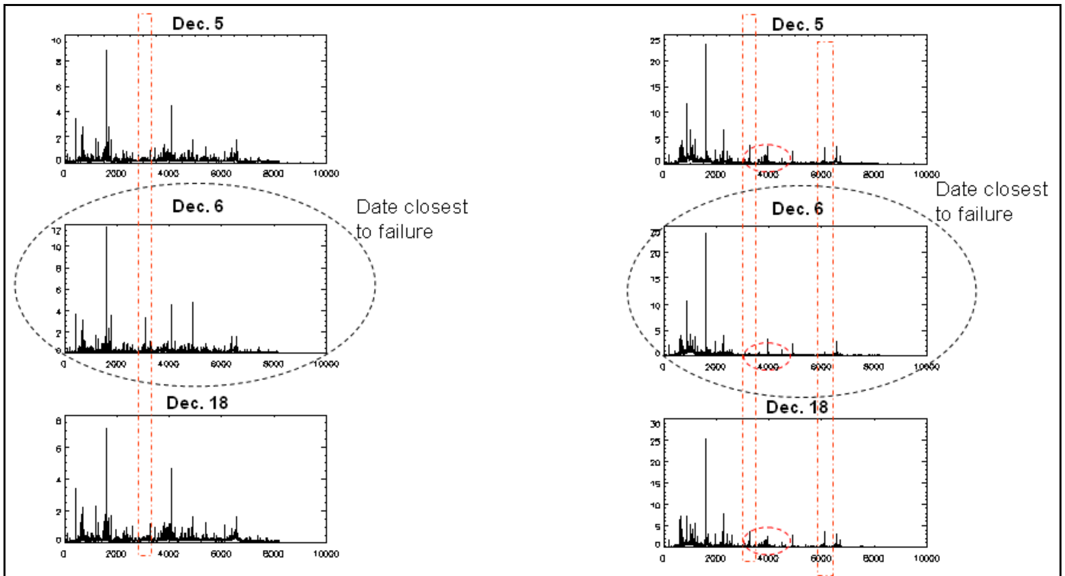
Date	Time	Condition
Dec. 2, 2005	13:01	Before fault, Fault 1
Dec. 2, 2005	15:45	Before fault, Fault 1
Dec. 2, 2005	22:58	Before fault, Fault 1
Dec. 3, 2005	01:35	Before fault, Fault 1
Dec. 3, 2005	02:37	Before fault, Fault 1
Dec. 3, 2005	02:50	Before fault, Fault 1
Dec. 3, 2005	03:06	Before fault, Fault 1
Dec. 3, 2005	03:17	Before fault, Fault 1
Dec. 3, 2005	12:13	Before fault, Fault 1
Dec. 4, 2005	00:28	Before fault, Fault 1
Dec. 4, 2005	22:10	Before fault, Fault 1

Table 1. Data available for fault diagnosis for Aircraft Tail number 5180 (continued).

Date	Time	Condition
Dec. 5, 2005	02:31	Before fault , Fault 1
Dec. 5 , 2005	13:06	Before fault , Fault 1
Dec. 5, 2005	21:58	Before fault , Fault 1
Dec. 6, 2005	22:14	Before fault , Fault 1
Dec. 17, 2005	23:11	After fault , Fault 1
Dec. 17, 2005	23:27	After fault , Fault 1
Dec. 18 , 2005	13:01	After fault , Fault 1
Dec. 18 , 2005	15:40	After fault , Fault 1

NOTES:
Failure date: Dec. 9, 2005
Table for fault 1 data

Since we were interested in components in the vicinity of the main transmission (hydraulic pumps), we selected (out of the data collected by 15 different sensors) the outputs from sensors "#1 Main GB" and "#3 Main GB". Stored spectra were available for all dates listed in the table, and sample spectra from the #1 Main GB obtained on Dec. 5, Dec. 6, and Dec. 18, 2005 (all from Fault 1 data) are shown in figure 1. We note that data for Dec. 6, the date closest to the failure, is qualitatively different than the other two. (We assume that the defect was corrected before the Dec. 18 measurement.) In particular, we notice the spectral bands indicated in the figure by the red box. A similar plot for #3 Main GB yields another spectral band of interest as indicated by the red box and oval in the plots of figure 2. In each case, the x-axis denotes Fast Fourier Transform (FFT) bin number.



(a) Spectra from "#1 MainGB" (b) Spectra from "#3 Main GB"

Figure 1. Indication of spectral bands of interest in the stored spectral HUMS data for the fault of interest.
Notes:
1. Dec. 6 is the date closest to component failure.
2. Units on the x-axis are FFT bin number.

2.2 CFAR-based CI Definition

Researchers have proposed several different CI (feature) definitions that capture anomalous behavior similar to that observed in figure 1. Some approach the problem using statistical techniques (*5*), others combine statistical approaches and physics-based data observations (*1*), while still others create physical models of the system in an effort to understand various faults (*6*). The CFAR-based approach that we propose is closest in spirit to the data-based methods because it relies on a set of training data to decide what is normal and abnormal system behavior. That is, a training set is used to set various algorithm parameters, in particular the detection threshold.

Like many of the CIs developed to date, the resulting definition is highly tailored to the specific failure mode of interest. Our goal is to develop a feature that will detect a specific, newly identified defect while maintaining an acceptably low probability of false alarm (Pfa); it is this philosophy that leads us to refer to the CI definition as CFAR-based.

We propose the following CI definitions based on empirical observations of data from #1 Main GB:

CI_1 (for fault 1):

$$CI_1 = \frac{\max\left(\left\|F_{test}(n_0 - B : n_0 + B)\right\|\right)}{\sqrt{\frac{1}{M_1}\sum_{i=0}^{M_1-1}\left\|F_{test}(n_1 : n_1 + i)\right\|^2 + \frac{1}{M_2}\sum_{i=0}^{M_2-1}\left\|F_{test}(n_2 : n_2 + i)\right\|^2}} \quad , \tag{1}$$

where $F_{test}(\cdot)$ is the HUMS spectrum for the test data, n_0 indicates the FFT bin number manifesting the fault, B is a small bandwidth allowing for frequency drift, n_1 indicates the starting FFT bin number for background region 1, n_2 indicates the starting FFT bin for background region 2, and M_1 and M_2 indicate the length of the spectral band (in bins) for background region 1 and background region 2, respectively. We base the selection of these frequencies of interest on the data sets enumerated in table 1 and illustrated to some extent in figure 1. The actual parameter values are determined empirically, utilizing a classical radar-based CFAR paradigm (*7*). Under these guidelines, n_1 and n_2 are selected to be "close" to n_0 while still allowing a "guard band" to provide some degree of separation. Thus, the quantity in the denominator of equation 1 represents a background average that also serves as a normalization factor, and the size of spectral peaks are measured relative to the local spectral background. This also enables our selected threshold value to be independent, to some extent, of differences in scale between different data sets. As a result, an empirically determined threshold value should suffice to achieve relatively low false alarm rates.

Based on initial experiments, we have determined that the values of M_1=150, M_2=150, n_0=3080, n_1=2800, n_2=3150, and B=20 (corresponding to approximately 60 Hz) provide acceptable results. It must be stressed, however, that these numbers are based on an FFT length of 8192 points, and a total available spectrum of approximately 24 kHz. If the total spectrum bandwidth and FFT length were to change, then the corresponding bin numbers and frequency band lengths (expressed in units of FFT bin) would also have to change. In addition, it should also be stressed that data collected in the Survey mode and FPG101 state were used for this analysis. It would be necessary to verify that the same phenomenology is evident before the same algorithm is applied to data collected in different data collection states (i.e., different from FPG101).

As a final note on the algorithm parameter definition and selection, we consider the motivation for including both the bandwidth, B, and the guard band around the test frequency bin. This decision is best understood by considering figure 2 below. The plots in figure 2 show that certain frequency bands may drift slightly from one data collection to the next; hence the maximum required by the numerator of equation 1 may not appear in the same bin from one data collection to the next. Hence, we need to include several bins around the frequency bin of interest to ensure that we capture the spike if it is present. Similarly, we include a guard band to ensure that we do not include sidebands due to the fault in our calculation of the spectral background.

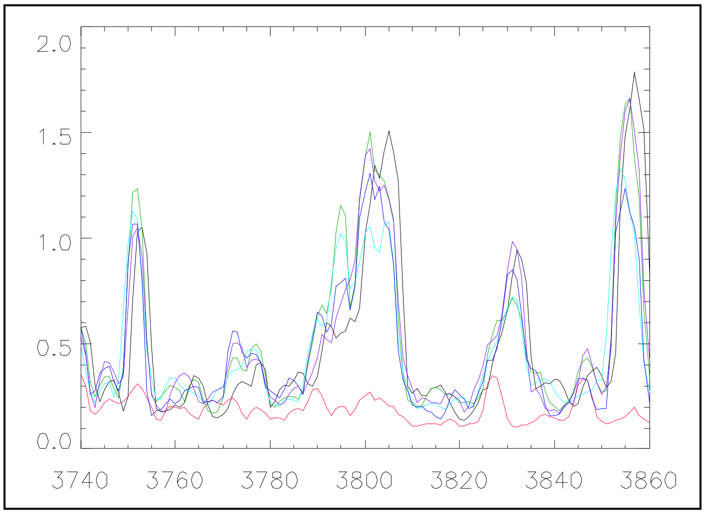


Figure 2. FFT output from different test runs for fault 1. Red plot indicates faulted data.

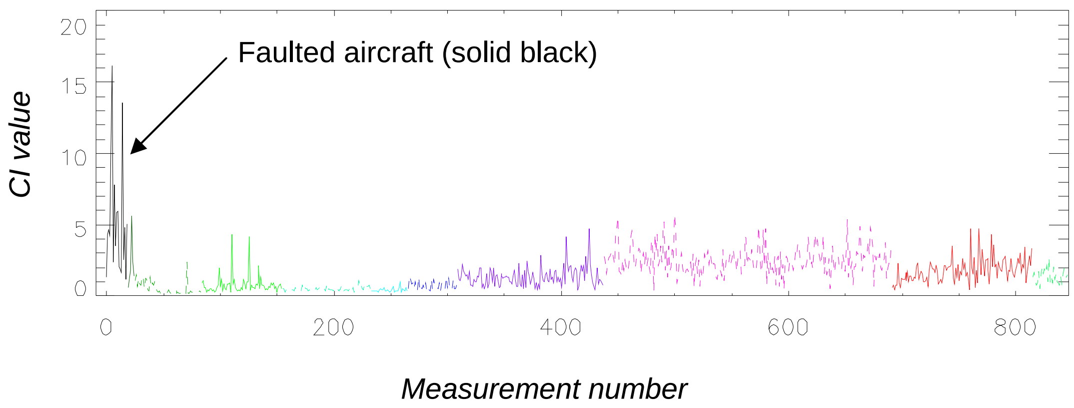
We have calculated feature values using all of the data from the faulted aircraft as well as un-faulted data from several other aircraft. These statistics are plotted and discussed in section 3.

3. Results

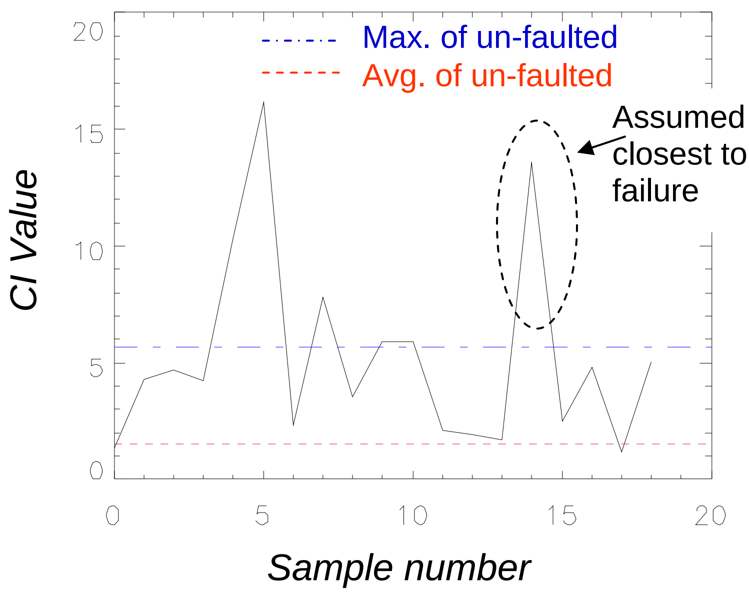
Figure 3 shows the feature values calculated for the faulted aircraft together with those calculated for a collection of non-faulted aircraft. The different aircraft are depicted by different line styles and colors, and for each of the aircraft the sample number increases with the date. That is, in figure 3(b), for example, sample 0 corresponds to Dec. 2, 2005, while sample 18 corresponds to Dec. 18, 2005. Note that there is no relationship between the data collection dates for the various aircraft, and the number of samples varies considerably from one aircraft to the next.

We can see from the plots that a threshold could be chosen such that none of the non-faulted aircraft would produce false alarms while the "faulted" aircraft would still be flagged before the failure date. In addition, there are several early measurements (taken before those closest to failure) that indicate a potential problem. This indicates that the weight of evidence could be brought to bear to increase confidence in the final decision.

We must note here that all of this analysis is based on a single failure example and utilizes field data collected as part of a specified operational testing procedure. By definition the amount of data available from such a collection protocol will be sparse. Hence, all of these results must be considered preliminary and doubtful until a statistically significant number of failure exemplars become available.



(a) Plot of all CI_1 values for 11 aircraft (including the faulted aircraft). The solid black lines indicate CI values from the faulted aircraft, while the different colors and line styles indicate other aircraft.



(b) Plot of CI_1 values for faulted aircraft. The dashed red line indicates the mean of all CIs from other aircraft, and the blue line indicates the maximum CI_1 from all other aircraft.

Figure 3. Plots of CI_1 for all aircraft (faulted and non-faulted).

4. Summary

We have presented a method for calculating condition indicators based on CFAR automatic target detection (ATD) concepts. This development yields a ratio test that—since it is a ratio of a test cell magnitude to a RMS background average—allows the user to set a threshold limiting the number of false alarms. We have exercised the algorithm using several fault-free data sets and observed that we could, indeed, set a threshold that detected the fault while avoiding false alarms. Since we only had access to a single example of the failure mode, these results must be viewed as preliminary.

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Acronyms

AMRDEC	U.S. Army Aviation and Missile Research Development and Engineering Command
ARL	U.S. Army Research Laboratory
ATD	automatic target detection
CBM	condition based maintenance
CFAR	constant false alarm rate
CI	condition indicator
FFT	Fast Fourier Transform
HUMS	Health and Usage Monitoring System
Pfa	probability of false alarm

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