Advancement of Aging Rotorcraft Predictive Maintenance through Rationalization of Condition Monitoring and Data Analysis Techniques

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Abstract:

This paper outlines ongoing and future efforts put forward by the Condition-Based Maintenance (CBM) Research Center at the University of South Carolina to improve diagnostic and prognostic capabilities of Digital Source Collector (DSC) systems (Vibration Management Enhancement Program (VMEP), Modern Signal Processing Unit (MSPU), and Integrated Health Monitoring System - Health Usage Monitoring System (IVHMS-HUMS)) by rationalization of condition monitoring and data analysis techniques for CBM of drive train components of AH-64 and UH-60 model aircraft. The proposed research is characterized by an advanced signal processing technique that can quantify degradation of the helicopter power train by use of the data collected from state-of-the-art HUMS. Furthermore, proposed techniques are being extended to other signals such as acoustic, electrical, and temperature, so data fusion techniques can be applied in order to improve diagnostic performance and statistically predict system’s failure for a proactive maintenance. Explained in additional detail is the continued effort to model the AH-64 test system to more fully and realistically represent the actual conditions and lifetime of aircraft using novel and advanced signal processing techniques such as time-frequency domain information measure to assess the test-bed’s mechanical and electrical systems’ health that could lead to localized faults encountered by actual military and civilian aircraft. Further methods of increasing the likelihood of fault detection are discussed, including data fusion from varied sensing methods, providing enhanced detection of exceeded performance thresholds while eliminating undesirable disturbances caused by false alarms in health monitoring systems.

1. Introduction

Condition-Based Maintenance entails detection of faults based on predictive condition indicators as opposed to standard time-based scheduling. An ongoing project at the University of South Carolina, supported by the South Carolina Army National Guard since 1998, aims to conduct tests of various rotorcraft parts and configurations for SCARNG, while gathering data to inform a point of comparison for current and future condition monitoring rationalization and analysis techniques. Introduced herein is a brief overview of experimental set-up for the Condition-Based Maintenance Center at USC as well as the steps of research leading toward one potential method for sensor data fusion, the time-frequency based mutual information measure. Quadrature and In Phase subsets of this measure provide a statistical characterization of part status potentially differentiating between unbalanced and misaligned states. The overarching objective
of the current CBM research is to combine useful data from various sensors such as acoustic, electrical, and temperature/thermocouple via sensor fusion so that a statistical prediction of a system’s failure can be achieved for proactive maintenance.

2. Experimental Setup and Data Description

2.1. Data Description

The CBM research center at the University of South Carolina has a simulated AH-64 apache helicopter tail rotor driveshaft (TRDT) assembly for collecting vibration, acoustic, and temperature data as well as miscellaneous torque and speed for control and further mechanical analysis. The shafts that control rotation are the military standard used in the AH-64 model helicopter with connecting bearing, flex coupling, and gearbox (intermediate and tail rotor) configurations. Input and output torsion are simulated by a main drive motor and absorption motor as shown described in the picture and computer designed illustration of Figure 2.1.1. Accelerometer data is gathered from the placements shown in Figure 2.1.1(b) with sensor separation between accelerometer signal, S1, and signal, S2, at 3.43 meters. Thermocouples are similarly placed with additional sensors on the intermediate and tail rotor gearboxes. Acoustic data can be obtained from constant video monitoring of test stand operation, parsed from video files.

![Figure 2.1.1: Tail Rotor Drive Train in the CBM test center at USC (a) and Schematic Diagram (b).](image)

The TRDT test stand described earlier monitors two sets of signals important to the proposed vibration analysis, mutual information measure. These signals are referenced as S1, indicating the forward hanger bearing signal, and S2, the aft hanger bearing signal. The signals given by the accelerometers were sampled at 48 kHz over a span of typically 160-180 ms. A typical experimental run would have 8196 samples or more. For our tests and measures, we will consider a baseline shaft, a shaft with unbalanced load, a misaligned shaft, and combinations of these two differing effects focused on differing degrees of misalignment in the drive train. Discussion follows to illustrate that classical analysis using FFTs and time-frequency analysis is helpful in understanding our physical system but can be improved upon by methods such as statistical and numerical analysis using the developing self and mutual information measures [1-3].

2.2. Physical Definitions

We will analyze how actual physical processes in the drive-train lead to the presented results of the mutual in-phase and quadrature information, and correlate to the clustering patterns (Figure
2.2.1). Here excessive unbalance and misalignment are considered as the main components of damaging forces/vibrations/wear in the rotordynamic system.

Unbalance forces/vibrations are generated when geometrical centerline or mass centerline of a shaft do not coincide with rotational axis of the shaft (bearing looseness, manufacturing imperfections). This creates uniform eccentric force/bow \( F_u \) of the shaft, which can be represented as a rotating force vector perpendicular to the shaft rotation axis, which has varying magnitude, but the same phase angle \( \phi \) along the shaft (Figure 2.2.1a, b).

![Figure 2.2.1: Unbalance force distribution over the shaft supported at the S1 and S2 accelerometers locations (a), cross-section of a bearing and the shaft at the S1 accelerometer location (b), shaft centerline orbits at the S1 and S2 accelerometers locations, and displacement/vibration components in the x and y axis directions (Du, Dm1 orbits when \( \phi_y - \phi_x = 90 \), Dm2 when \( \phi_y - \phi_x = 120 \)).](image)

It creates harmonically varying displacement/vibrations \( D \) on a hanger bearing raceway/housing, which are registered by dedicated accelerometers. Theoretically we can have internal \( x \) and \( y \) axis radial vibrations, \( z \) axis axial vibrations, and torsional vibrations of a shaft in a bearing (fig x b) (besides vibrations coming from coupled bearings, gearboxes, power units, airframe, etc.). Each shaft support/hanger bearing on a helicopter has only one dedicated accelerometer, which can pick only lateral \( x \) axis component of the vibrations (Figure 2.2.1c):

\[
\begin{align*}
D_x &= A_x \cos(\omega t + \phi_x) \\
D_y &= A_y \cos(\omega t + \phi_y)
\end{align*}
\]

where \( D_{x,y} \) and \( A_{x,y} \) are displacements and amplitude of displacements in \( x \) and \( y \) axis directions, \( \omega \) - angular velocity, \( \phi_{x,y} \) - phase angles.

Vibrations caused by unbalance will be in-phase on both bearings accelerometers \( S_1 \) and \( S_2 \) (\( \phi_y - \phi_x = 0 \)), and will vary only in magnitude depending on the magnitude of unbalance \( F_u \), which is shown by constant quadrature component and varying in-phase component of the mutual information measure (Figure 2.2.1).

Shaft supported by the hanger bearings at sensor locations \( S_1 \) and \( S_2 \) is not a uniform shaft – it is made of sections, and coupled by flex couplings at the bearings locations, so there is a possible misalignment which cannot be avoided. Misalignment in our case is considered as an angular misalignment when the shaft centerlines of the two shafts meet at angle with each other. This, on the contrary to unbalance, causes axial preloads on the shaft in the \( z \) axis direction, and can be decomposed to \( x \) signal component based on angle of misalignment \( F_x = F_z \sin(\phi_m) \). This force will have the greatest impact on the bearing closest to the shafts coupling point, and will have a
phase difference in reference to force registered at a further located sensor \( (\varphi_y - \varphi_x \neq 0) \) (Figure 2.2.1c), because of finite stiffness and dampening in the system. That is why we observe constant in-phase component and varying quadrature information component in case of misalignment (Figure 2.2.1).

Full system is much more complex, because of all the vibrations/noise sources and higher harmonics superimposed over unbalance and misalignment signal, generating multi frequency-phase vibrations, which should not be analyzed/interpreted separately of each other. In industry one would use more recognized shaft diagnosis technique as shaft centerline orbit monitoring, which requires two \( x \) and \( y \) sensors at a single location, and a skilled human operator, which make such technique inapplicable in our case and justifies the need for an advanced diagnostic measure. Mutual information measure takes advantage of two accelerometer signals located at different locations, simultaneously quantifying all frequency and phase components of the mechanical vibrations signals.

2.3. Motivation

Classical signal analysis in the frequency domain (such as that accomplished by FFTs or cross power spectral density) assumes stationary signals in the time domain. It is a reasonable assumption for the steady-state normal operations of a system, but the abnormal condition of the system is characterized by non-stationary or transient signatures in the time and frequency domain. Hence, in the treatment of a transient signature whose periodicity with respect to the fundamental frequency cannot be defined, it is necessary for us to consider the time and frequency domain simultaneously. Time-frequency analysis is motivated by the analysis and representation of non-stationary signals whose spectral characteristics change in time [6].

The power spectrum can be obtained for the CBM data and will be shown as a point of comparison for further time-frequency analysis as illustrated in Figure 2.3.1. Frequency content is shown with dominant frequencies of S1 and S2 highlighted. From the visible frequency content, slight changes in the signal harmonics can be seen based on vibration data of different machine states, however, the spectra still look fairly similar and the frequency shifting and power loss in low harmonics remain unsure indication of change. Variations over short time intervals can not be seen, with power in the respective frequency bands being measured over the full time interval.

Figure 2.3.1: Power Spectral Density
Therefore, in the proposed research, we will utilize time-frequency analysis, which provides simultaneous time and frequency information for the analysis and assessment of transient disturbance signals. This is under the given assumption that all vibration analysis for mechanical component diagnosis and prognosis is performed in time and frequency domain, while time-frequency domain analysis is performed in a large time scale for vibration level trending or order analysis by a professional human expert. The primary innovation in the proposed work is that time-frequency analysis will be performed on very short time scale signals, representing all the transients of the time signal. As a result, one can extract “meaningful” parameters such as instantaneous frequency, group delay and Rényi information [11], which will be a key factor in the proposed research, for a quantitative description of transient signal. Thus, one can take great advantage of time-frequency analysis for the scientific investigations of transient or non-stationary signals, achieving a more robust system description than descriptions from classical analysis.

3. Proposed Technique: Time-Frequency based Information Measure

It is advantageous to visualize the time-varying spectral characteristics of a transient signature. However, without post-processing of the time-frequency distribution, the task of achieving diagnostics and prognostics is not an easy one and requires quantitative health assessment. Thus, it is necessary to find a mathematical measure of the time-frequency distribution that characterizes the “physics” of the signal. Williams, Brown, and Hero proposed a measure of time-frequency information by use of the generalized Rényi information [12]. The definition of the generalized Rényi time-frequency information is defined as follows:

\[
H_\alpha(C_s) = \frac{1}{1 - \alpha} \log_2 \frac{\int \int C_s^{\alpha}(t, \omega)dt d\omega}{\int \int C_s(t, \omega)dt d\omega}
\]

where the time-frequency distribution is obtained from a Cohen’s class time frequency distribution.

The Rényi information measure is a meaningful measure of time-frequency distribution, but it is only defined for a single realization of a signal, e.g. self-information [8]. If a pair of signals closely related is to be examined, how can we define or quantify the interactions in terms of mutual information? In order to analyze the information of two closely spaced components, for example the S1 and S2 signal pair, the classical mutual information of two random processes is extended to two time-frequency distribution functions.

Let us consider the classical definition of the mutual information that might be extended to the measure of mutual information of the time-frequency distributions. The joint entropy \(H(X;Y)\) of a pair of continuous random variables \(X, Y\) with a joint probability density function \(p(x; y)\) is defined as:

\[
H(X, Y) = - \int \int p(x, y) \log_2 p(x, y) dx dy
\]

The joint entropy can be described by conditional entropy and self entropy such that:

\[
H(X, Y) = H(X) + H(Y | X)
\]

where \(H(Y | X)\) is the conditional entropy. Under the same conditions, the mutual information \(I(X;Y)\) is the relative entropy between the joint distribution \(p(x; y)\) and the product distribution of the individual marginal distribution \(p(x)\) and \(p(y)\) as follows:
The mutual information can be described in terms of self and joint entropy as follows:

\[ I(X; Y) = H(X) - H(X|Y) = H(Y) - H(Y|X) = H(X) + H(Y) - H(X, Y) \]

These basic definitions of mutual information from probability analysis can then be extended and applied to the time-frequency distributions. Figure 3.1 summarizes and illustrates the relative entropy in relation to the conditional entropy as well as providing a slightly more detailed application of the mutual (cross) and self information of the normalized method in the time-frequency distribution. This normalized mutual information is complex valued and is thus relatable as a component of real and imaginary valued expressions.

Figure 3.1: Classical conditional and relative entropy definitions with time-frequency application.

Summarizing, the time-frequency mutual information will measure the degree of mutual information allocated in in-phase and quadrature components. The in-phase and quadrature components are related by the time delay between two time series. This feature of the proposed technique will be beneficial because the time-frequency signature of the vibration signal is characterized by time-varying multiple frequency components, which makes it extremely challenging to analyze the signal with classical time-frequency analysis techniques.

4. Failure Analysis with Time-Frequency Analysis

4.1. Vibration Signal Analysis

As discussed, time frequency analysis of the vibration signals, S1 and S2, yields a visibility of time varying frequency or harmonic content. In Figure 4.1.1, a set of spectrograms of S2 are provided for the baseline shaft and the shaft with unbalance loads. This can be compared to the
power density spectrum of Figure 2.1.1. The top portion of the figure is the signal time series and its time-frequency distribution is provided in the same time axis, while the traditional energy spectral density is provided in the left corner of each figure. Based on the time-frequency distributions provided in Figure 4.1.1, one can quantify physical parameters like instantaneous frequency and bandwidth. The number of signal elements on the time-frequency plane can be mathematically assessed by information measure.

It is notable that the traditional energy spectral density plots look almost identical in the frequency domain, but the vibration signatures in time-frequency domain exhibit distinctive characteristics. For example, two distinct frequency stripes can be seen in the aft hanger bearing readings. The higher of these frequency stripes (1500-2000Hz range) is not found on the forward hanger bearing. This frequency stripe is attributed to frequencies emanating from the tail rotor gearbox. The distinguishing diagnostic indicators found from the spectrogram are related with differences related to the forward hanger bearing signal. The major differences in the forward hanger bearing reading between the balance and unbalance cases revolves around the increases in power related to the 5 kHz and 15-20 kHz bands. These differences cannot be distinguished from the traditional power spectrum reading but are made very apparent from the reading of the spectrogram.

Next, application of the proposed Mutual Information measure on the signals S1 and S2 yields further quantification of machine state. The Mutual Information, a complex value, can be split into two subsets: the In Phase and Quadrature measures. For Figure 4.1.2 a scatter plot is made of these measures with the In Phase Information on the x-axis while the Quadrature Information is reported on the y-axis for various system configurations. Each point represents a separate window of data with each system setting containing 272 points of data. The common measurement in these plots is the Mutual Information between S1 and S2 sensors for these varied system configurations while the common comparison is the mutual information of S1 and S2 for the baseline case.
These results show a tendency of the unbalanced shaft test Mutual Information to skew in the negative In Phase direction while the misaligned shaft test Mutual Information tends to skew toward the negative Quadrature direction. Both of these directional tendencies are taken with respect to the baseline cluster, resulting in a measure that could show sensitivity to slight changes in machine state from a standard or modeled norm with quantifiable parameters. The combination tests of unbalanced and misaligned conditions show aspects of both tendencies, with Mutual Information points spreading along the In Phase axis as well as the Quadrature axis. Further testing will focus on varying degrees of misalignment and unbalance to see if the difference in machine state is truly quantifiable and if so how sensitive this measure is to system variation. A method must be derived to indicate acceptable levels of variation.

One proposed method would be a statistical analysis of the Mutual Information measure. Statistical characterization could rely on the mean value of a mechanical system’s mutual clustering. Distance relative to the baseline standard deviation provides useful statistical quantification. Table I presents mean, variance, standard deviation, and correlation coefficient for each setting; Baseline, Unbalanced, Misaligned, or a Combination of unbalanced and misaligned states.
Table I. Mutual Information Statistical Summary

<table>
<thead>
<tr>
<th></th>
<th>00321 Baseline</th>
<th>10321 Unbalanced</th>
<th>20321 Misaligned</th>
<th>30321 Combined</th>
<th>40321 Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (μ)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Phase</td>
<td>1.1226</td>
<td>-0.8143</td>
<td>0.4928</td>
<td>-0.9147</td>
<td>-0.1457</td>
</tr>
<tr>
<td>Quad</td>
<td>0.4614</td>
<td>-0.5425</td>
<td>-1.3321</td>
<td>-0.3041</td>
<td>-0.0680</td>
</tr>
<tr>
<td>Variance (σ²)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Phase</td>
<td>0.0781</td>
<td>3.6678</td>
<td>0.0455</td>
<td>0.9277</td>
<td>2.0265</td>
</tr>
<tr>
<td>Quad</td>
<td>0.0487</td>
<td>0.4528</td>
<td>1.6147</td>
<td>0.1873</td>
<td>1.5387</td>
</tr>
<tr>
<td>Standard Deviation (σ)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Phase</td>
<td>0.2795</td>
<td>1.9152</td>
<td>0.2134</td>
<td>0.9632</td>
<td>1.4235</td>
</tr>
<tr>
<td>Quad</td>
<td>0.2208</td>
<td>0.6729</td>
<td>1.2707</td>
<td>0.4328</td>
<td>1.2405</td>
</tr>
<tr>
<td>Correlation Coefficient (ρ)</td>
<td>From Covariance</td>
<td>0.1905</td>
<td>0.9668</td>
<td>0.1161</td>
<td>0.5384</td>
</tr>
</tbody>
</table>

From this analysis of the mutual information measure shifts in the mean along the negative in phase and quadrature axes indicate change in machine state from baseline to misaligned or unbalanced states. Variation along the in phase axis shows promise as an indicator of imbalance with a much larger variance and standard deviation reported in the mutual information. The displacement of mean value in the negative direction of the quadrature axis and increase in quadrature variance and standard deviation can be developed to indicate misalignment. In cases where the mechanical system is both unbalanced and misaligned the possibility of further quantification is evident from the 30321 and 40321 cases where the 40321 case shows larger variance in both the in phase and quadrature measures than the less severe 30321 combined unbalanced, misaligned case. Further research will focus on varying states of misalignment and unbalance to allow quantification of these states.

4.2. Transmission Gearbox

A preliminary time-frequency investigation analyzed vibration data collected from the tail rotor gear box (TRGB) in lubricant starvation and resulting gear teeth metal-to-metal contact and significant wear. The AH-64 TRGB tested is a bevel spiral tooth gear, having a 22:57 transmission ratio, operating at approximately 3700 rpm input shaft speed. It was tested for durability under critical lubrication conditions (all grease was allowed to leak through a seeded fault output seal). The reasoning behind the study was that the output seal on the gearbox often starts leaking grease and it cannot be replaced in the field. Also, the procedure requires grounding of the helicopter and fixing the seal immediately after the leak is detected. It cannot be accomplished without removing the entire gearbox, which is a time consuming process and keeps the helicopter grounded in the event of a mission. The intent was to test performance and durability of the gearbox in case it is kept as is with the output seal leaking and see if it can last 250 hours until its scheduled maintenance date or end of a mission.
Figure 4.2.1: Time-frequency distributions focused on tail rotor gearbox (TRGB) harmonics over four consecutive days. Day #4 (bottom right) indicates failure of the TRGB

Figure 4.2.1 shows the time-frequency distribution over four consecutive days prior to failure. The first three plots of Figure 4.2.1 (#1 - #3) display great similarities in the 1-6 kHz bands while the last shows a shifted spectrum with a power increase in the 5 kHz region coinciding with the failure of the tail rotor gearbox later that day. Additional tests will allow for a closer description of condition-based faults. Examples such as this case display the efficacy of an enhanced focus on single component harmonics to refine the condition indicators currently used in identifying part health status via vibration analysis.

### 4.3. Acoustic Emission

Another case study focused on improving condition indicators comes from analysis of an acoustic signal. On the day of the failure, the experimental setup and its recorded video file were monitored. For an intellectual curiosity, we extracted the acoustic signal from the video file and examined the time-frequency signature of the data. Figure 9 displays the time-frequency analysis of part of the acoustic signal taken around the error event of the TRGB. This signal was collected with a sampling rate of 22,050 Hz and the time length was 16 seconds.

The short-time Fourier transform (STFT) and spectrogram used here for time-frequency analysis are both dependent upon the window type and length to determine the resolution in the time and frequency domains. To find the most accurate diagnostics with the best resolution, the signal was down-sampled 5 times and divided into 4 segments. Then, the appropriate hamming window resolution was selected with a size of 126. We found an exact time and frequency set which is highly related with the error of the TRGB.
The most noticeable observation is the frequency decrease during the 0~4 second interval and the significant frequency drop and oscillations in the two most dominant frequency terms (0.5 and 1 kHz) on the 4~8 second interval following the TRGB incident. The other noticeable facts are a decreased frequency region (0.3 and 0.7 kHz) and weaker stripe bands on 8~12 and 12~16 second intervals after the large oscillations of the 4~8 second interval. The diagnostic indicators found are thus: the decrease in the dominant frequency and oscillations in the two dominant frequency terms. The use of these indicators can be attributed to prognosis of the test stand error toward possible indication of preventive maintenance.

5. Conclusion

Aircraft component durability testing is an essential tool in CBM program development, supplying necessary calibration data for condition monitoring and diagnostic systems, and giving insights to design flaws and improvement possibilities. Time-frequency analysis offers new and
improved ways to assess faulting conditions in vibration signal analysis. It can be seen from Figures 4.1.1, 4.2.1, and 4.3.1 that time frequency analysis aids in identifying short duration transients and time varying harmonics critical to health monitoring. Extending this joint time-frequency analysis, the proposed mutual information measure allows an assessment of part state. The in-phase and quadrature components are related by the time delay between two time series. This feature of the proposed technique is beneficial to the aging aircraft diagnostic efforts, because the time-frequency signature of the vibration signal is characterized by time-varying multiple frequency components, which makes it challenging to analyze the signal with classical time-frequency analysis techniques when these harmonics can vary slightly over time or be affected by transient signals. The measure tends to show misalignment through increased scattering in the negative quadrature direction of the quadrature-in phase plane while showing unbalance by increased scattering in the negative in phase direction. The multi-sensor implementation of health system analysis using spaced vibration sensors, acoustic, vibration, electrical, and temperature sensors allows for a more robust rationalization of CBM data. Data fusion remains a possibility when multiple monitoring systems and sensors are employed, providing an opportunity to enhance and accelerate impending problem diagnosis and CBM system development. With data fusion implemented, the confidence level of preventive maintenance rationalization can be increased with more independent points of comparison. False positives can be eliminated and maintenance decisions may be enhanced using the proposed mutual information measure method.

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Reference


