REVIEW OF VIBRATION-BASED HELICOPTERS HEALTH AND USAGE MONITORING METHODS

Victor Giurgiutiu, Adrian Cuc, Paulette Goodman

University of South Carolina, Department of Mechanical Engineering

Columbia, SC 29208

Abstract: The purpose of this paper is to review the work that has been done in the past years by various researchers in vibration based health and usage monitoring and to identify the principal features and signal-processing algorithm used to this purpose. The damage detection concepts and the signal analysis techniques will be reviewed and categorized. Latest advances in signal processing methodologies that are of relevance to vibration based damage detection (e.g., Wavelet Transform and Wigner-Ville distribution) will be highlighted. These vibration signal-processing methods play an important role in early identification of incipient damage that can later develop in a potential threat to the system functionality, and even a flight accident. In aerospace applications, HUMS capabilities are to minimize aircraft operation cost, reduce maintenance flights, and increase flight safety.

Key Words: HUMS; Wavelet Transform; Wigner-Ville distribution; O&S; Machinery Failure Prevention; Neural Networks; Helicopters

INTRODUCTION

Machinery Failure Prevention is an important component of the maintenance activity for most engineering systems. Helicopters are continuously subjected to periodic loads and vibration environments that initiate and propagate fatigue damage in many components. Current helicopter maintenance practice requires a large number of parts to be monitored and replaced at fixed intervals. This constitutes an expensive procedure that adds considerably to the helicopter Operational and Support (O&S) costs. Health and Usage Monitoring Systems (HUMS) have been developed in recent years to detect incipient damage in helicopter components, predict remaining life, and create the premises for moving over from scheduled based maintenance to condition based maintenance. Of prime importance in such a HUMS system is the capability to evaluate the damage or undamaged state of a critical component using only the vibration data signals recorded during flight and ground operation. With such capability, the need for frequent disassembly and bench checking of certain critical components can be reduced and ultimately eliminated, with important ancillary savings in the O&S costs. However, to achieve such capability, advance vibration signal processing algorithms are necessary that can distinguish the damage related features from the background and system noise perturbations. Enhancements such as signal averaging, cepstrum and kurtosis analysis, time-frequency domain analysis, Wavelet transform, neural network systems have shown promising results (McFadden, 1985; Monsena, 1994). However, the challenge remains to translate this knowledge into fault prediction.

The earliest work toward detecting defects in helicopter gearboxes used a high-resonance technique and was a *off-line* monitoring tool focused on finding the exact location of the defect. Based on this technique, the frequency spectrum of the vibration signal is search to find a change in the spectral line at one particular frequency associated with any particular faults. This method has proved good results for simple bearing configurations but is not satisfactory for complex configuration or for a large damage (McFadden, 1985)

Fraser and King (1990) using kurtosis observed that when a gearbox component is severely damaged multiple impulses will appear in the frequency domain, resulting in a cumulative response that tend to reduce the kurtosis value. Another approach is to apply cepstrum based techniques, in an attempt to condense the frequency domain information into an easier to interpret form, thus providing a practical system for routine prognostic monitoring.

Forester (1990) demonstrates that time-frequency techniques, such as Wigner-Ville distribution can describe how the spectral content of the signal is changing with time and provided a framework for developing robust detection and classification schemes for helicopter gearbox faults.

WAVELET TRANSFORM METHOD FOR HELICOPTER HEALTH MONITORING

The wavelet transform is a signal-processing tool, which allows both the time domain and frequency domain properties of a signal to be viewed simultaneously. Performing a wavelet transform consist of convolving the signal with time shifted and dilated. The result of wavelet transform will be a set of coefficients, which are function of time and frequency, also called scale. These coefficients can be used to form a unique mean square wavelet map, a time-frequency representation of the signal.

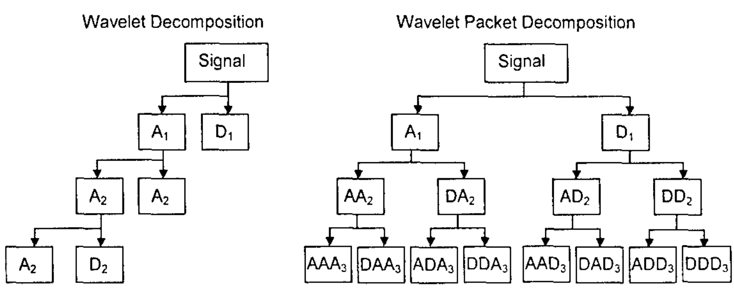

Figure 1 A comparison of the DWT algorithm and the DWPT algorithm. A_i is approximation at level i (low frequency) and D_i is detail at level i (high frequency). (Samuel et al., 1998)

Mallat (1988) discovered a recursive algorithm to compute the DWT consisting in basic wavelet function to form sets of filters, each one consisting of lowpass and highpass filter. The signal is pass through the first set of filters and the result will be two signal each with half of number of coefficients as the original signal. The signal formed using the lowpass filter and thus containing the low frequency information is known an the approximation, and the second signal formed using the high pass filter and thus containing the high frequency information is known as the detail. For the second recursion the approximation is passed through the next set of filters and so on until an approximation and detail each consisting of one coefficient are formed.

Newland (1993) presented the harmonic wavelet basic function, which is a smooth wavelet providing high numerically accuracy in signal reconstruction and it is completely band limited in the frequency domain. A consequence of the above is that DHWT need not be restricted to octave frequency bands. This form of DWT is known as the discrete harmonic wavelet packet transformation (DHWPT). The algorithm to compute DHWPT is the Mallat recursive algorithm and a comparison between the two algorithms is presented in Figure 1

Samuel et al. (1998) collected and analyzed data from an OH-58A main rotor transmission. The test was run at 6060 rpm (100% of the maximum speed), which resulted in a mesh frequency of 573 Hz, for nine days, eight hours per day at a 117% design torque as part of an accelerated fatigue test. The results were represented in mean square DHWPT maps. The mean square wavelet maps clearly shown the presence of the fault in day nine. Using the normalized power computed for the mash frequency and its accompanying frequency bands the evolution of the fault from day one to day nine was identified (Figure 2a).

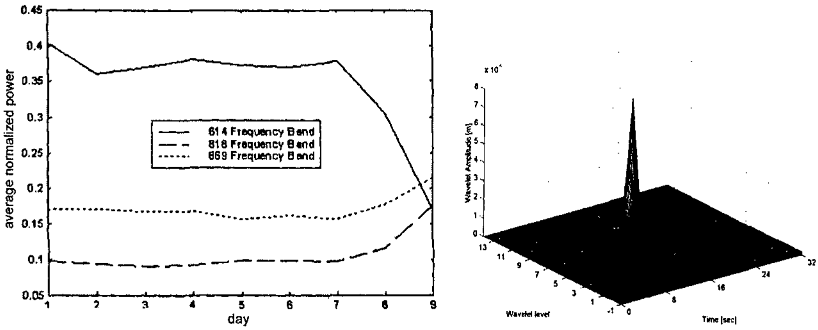

Figure 2 (a) Average normalized power index (Samuel et al., 1998); (b) Directional harmonic wavelet map: 10% crack with 5% noise (Kim and Ewins, 1999)

Kim and Ewins (1999) applied the directional harmonic wavelet transform (DHWT) to investigate the transient vibration response using a numerical simulation of a rotor system during the run-up period with a speed ramp rate of 100[rpm/sec] for the case of a rotor with 10% crack (transverse) depth relative to its diameter. To validate the advantages of DHWT, short time Fourier transform (STFT) was applied to the same set of data (noise contaminated signal). The results presented in Figure 2b reveal the advantage of DHWT over the STFT, because the results from DHWT are insensitive to the random noise while the STFT provides noise-contaminated results (Kim and Ewins, 1998).

NEURAL NETWORK-BASED AND NEURO-FUZZY HELICOPTER HEALTH MONITORING

A common trend in the recent technology and applied research efforts is to create smart systems that are capable of self diagnosis, assessment of self efficiency and operating condition, adaptation, and may be even self remedy. One source of inspiration for researchers is the human body. Studies of the microstructure of the nervous system and the decision making process of the humans have lead to the new concepts as neural network and neuro-fuzzy logic.

Monsena and Dzwonczyc (1995) proposed a hybrid (digital/analog) neural system as an accurate off-line monitoring tool used to reduce helicopter maintenance costs, and an all analog neural network as a real time helicopter gearbox fault monitoring. The hardware platform used is an analog neural network platform, Integrated Neural Computing Architecture (INCA/1). The vibration data were generated using an intermediate gearbox known as the Hollins TH-1L 42-deg tail rotor. Vibration data was recorded from two Endeveco 2220C accelerometers. A low pass filter with a cutoff frequency of 10 kHz was applied when data was generated. The main objectives of the hybrid and analog neural network are: fault detection, fault classification and fault identification. A comparison between the capability of the hybrid neural network to detect faults and the analog neural network is presented in Figure 3. The results indicate that a system employing 60-point DFT was capable of solving the fault detection problem. For the fault classification and identification problem, a 256-point DFT was required for perfect system performances. The performance results by using the all-analog neural network suggest that it is possible to achieve 100% fault detection with 0% false alarm rate.

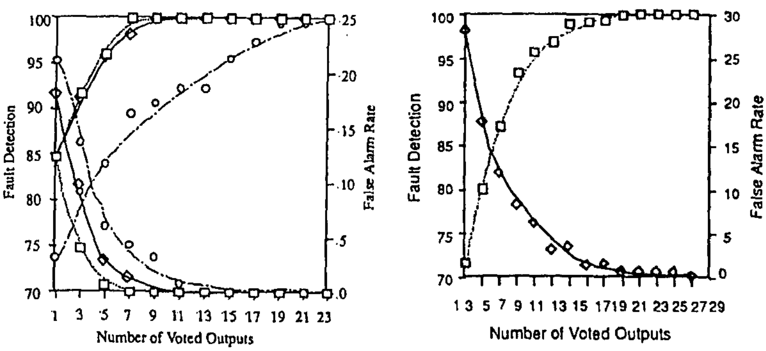

Figure 3 (a) Hybrid neural networks system performance, o = 60-point DFT, ◊ = 128, = 256; (b) All analog system performance, fault detection, ◊ = false alarm (Monsena and Dzwonczyc, 1995)

Essaway et al. (1998) presented an automated predictive diagnosis (IPD) techniques for monitoring the health of helicopter gearboxes. This technique is based on neuro-fuzzy algorithms for pattern clustering, pattern classification, and sensor fusion. The vibration data used was obtained from an aft main power transmission of a CH-46E helicopter. Frequency domain and wavelet analysis techniques were used to analyze the data and prepare them for the neural network inputs. To train the neural network, a non-supervised learning algorithm known as Self Organizing Maps (SOM) was used. A feedforward backpropagation neural network was used to classify the different faults. In the preprocess part of the vibration data, both auto power spectral density (APSD) and wavelet coefficients were used. A list of the fault types is presented in Table 1. The results obtained using the first feature extraction method (129 points APSD) and second extraction method (wavelet transform) are promising and they are presented in Table 2 and Table 3. These results show that the neuro-fuzzy technique using both APSD and wavelet transform, even though classification results was not perfect for all sensors, produced 100% classification for all cases.

Table 1 List of the fault types created in the test gearbox (Essaway et al., 1998)

Fault #	Fault type	Fault #	Fault type
Fault 2	Planetary bearing corrosion	Fault 6	Helical idler gear crack propagation
Fault 3	Input pinion bearing corrosion	Fault 7	Collector gear crack propagation
Fault 4	Spiral bevel input pinion spalling	Fault 8	Quill shaft crack propagation
Fault 5	Helical input pinion chipping	Fault 9	No defect

Table 2 Neural Network Classification results using APSD features at 100% load (Essaway et al., 1998)

Fault	Load		Acc1	Acc2	Acc3	Acc4	Acc5	Acc6	Acc7	Acc8
Fault 2	100%	Train	100%	100%	100%	100%	100%	100%	100%	100%
		Test	100%	100%	100%	100%	100%	100%	100%	100%
Fault 3	100%	Train	100%	100%	100%	100%	93.3%	90%	100%	100%
		Test	100%	100%	100%	100%	90.9%	100%	100%	100%
Fault 4	100%	Train	100%	100%	100%	100%	86.7%	100%	100%	100%
		Test	100%	100%	100%	100%	81.8%	100%	100%	90.9%
Fault 5	100%	Train	100%	100%	100%	100%	70%	93.3%	100%	96.7%
		Test	100%	100%	100%	100%	72.7%	100%	100%	100%
Fault 6	100%	Train	100%	100%	100%	100%	80%	76.6%	100%	100%
		Test	100%	100%	100%	100%	27.3%	90.9%	100%	100%
Fault 7	100%	Train	100%	100%	100%	100%	100%	93.3%	100%	100%
		Test	100%	100%	100%	100%	100%	90.9%	100%	90.9%
Fault 8	100%	Train	100%	100%	100%	100%	96.7%	83.3%	100%	100%
		Test	100%	100%	100%	100%	81.8%	63.6%	100%	100%
Fault 9	100%	Train	100%	100%	100%	100%	90%	93.3%	100%	100%
		Test	100%	100%	100%	100%	63.6%	100%	100%	81.8%

Table 3 Nural network classification results using wavelet features (Essaway et al., 1998)

Accelerometer#	Fault2	Fault3	Fault4	Fault5	Fault6	Fault7	Fault8	Fault9
Acc 1	100%	100%	66.67%	100%	100%	100%	100%	88.89%
Acc 7 (14x14 SOM)	100%	88.89%	88.89%	100%	100%	100%	100%	100%
Acc 7 (9x9 SOM)	100%	88.89%	44.44%	100%	100%	100%	100%	100%

JOINT TIME-FREQUENCY WIGNER-VILLE DISTRIBUTION ANALYSIS TECHNIQUES

The signal processing methods for machine-health monitoring can be classified into the time-domain analysis, the frequency-domain analysis, and joint time-frequency domain analysis. Some of the parameters used in those methods are FM0, FM4, NA4, NA4*, NB4 and NB48* (Polyshchuk *et al.*, 1998). The Wigner-Ville distribution (WVD) is a joint time-frequency signal analysis. The WVD is one of the most general time-frequency analysis techniques, as it provides excellent resolution for accurate examination in both time and frequencies domains. Some of the problems encounters in using WVD are related to the aliasing arising in the computation of WVD and to its the nonlinear behavior. To avoid the aliasing problem, the original real signal is transformed into the complex analytical signal. Polyshchuk *et al.* (1998) used the WVD techniques, introducing a new parameter, NP4, to experimental data obtained from a helicopter-tail gear transmission. The damage introduced is single-tooth damage in the tail gear. The WVD and the instantaneous power plot for an undamaged gear were analyzed. Two large components, the first and second harmonics of the gear-mesh frequency, were identified. For a damaged gear, the WVD and the instantaneous power plot were found to be quite different (Figure 4). A clear peak was identified in the WVD and power spectrum density (PSD) plots. This peak was not present in the WVD and PSD plots of the undamaged case. These results proved that the use of WVD could be a good tool in fault detection and failure prevention.

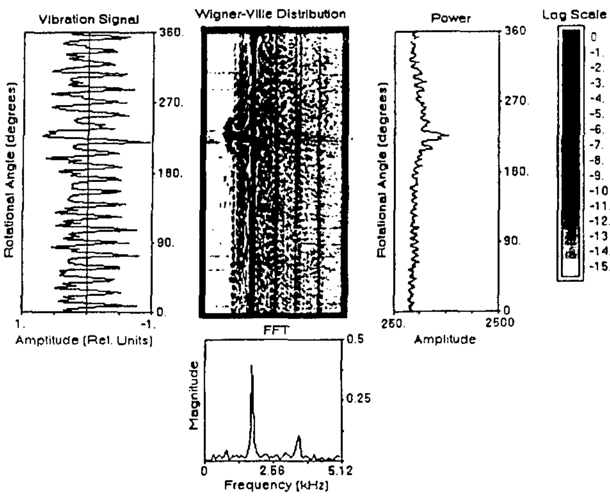

Figure 4. Accelerometer data for damaged gear (Polyshchuk et al., 1998)

VIBRATION ANALYSIS EDUCATION SOFTWARE

Successful predictive maintenance programs will enable an organization to reduce maintenance cost, reduce unscheduled down time, reduce catastrophic failures, improve safety and decrease maintenance man-hours. The keys to a successful condition-monitoring program are accurate prediction of machine faults, accurate repair recommendations, automation (to reduce human error), a refined reporting system and ease of operation and use. Commercial vendors, realizing the importance of creating sound maintenance programs, have

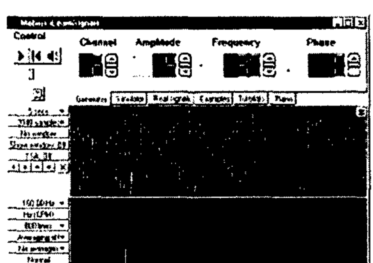

Figure 5 Mobius iLearn Interactive vibration signals.

introduced software programs and products to combat the high cost and complexities involved with equipment maintenance. In recent years due to the changes in technology, software now exists that is capable of exploiting vibration analysis algorithms and data analysis functions, presenting data with a user-friendly graphical user interface. Broadband and narrowband statistical analysis, complete spectrum normalization, trending, automatic peak identification, user selectable warning/alarm level functions are only some of the features offered in vibration analysis software today. This section will comparatively examine three different packages that allow vibration analysis, as well as a computer based training (CBT) programs.

MOBIUS ILEARN INTERACTIVE

In order to be more effective when monitoring a maintenance program, the end user should understand the actual signals being collected to properly interpret the results. A thorough understanding of the relationship between the machine and the characteristics observed will enable the end user to make educated interpretations. Mobius iLearn Interactive is a practical and theoretical training tool, useful to anyone interested in condition monitoring and vibration analysis, regardless of his or her experience in the field. The CBT is self-paced, incorporating simulations, animations, and samples of real data and diagnostic requirements – creating a realistic, interactive, and valuable learning tool. The complete curriculum is split into five, non-progressive, separate modules:

- iLearn Vibration — condition monitoring and vibration analysis learning is narrated while the end user interacts with diagrams and simulations.
- iLearn Hands-On – is a set of vibration measurements taken from a fault test rig. Over two hundred tests covering dozens of fault conditions are analyzed. Analysis can be done on the screen or downloaded into the end users data collector.
- iLearn Case Histories – is a library of spectra and waveforms taken from real machines. Digital recordings enhance the vibration analysis experience. Analysis can be done on the screen or downloaded into the end users data collector.
- iLearn Signals – is a virtual signal generator and spectrum analyzer. This software program will generate simple signals to teach waveforms and spectra. Advanced capabilities delve into signal processing.
- iLearn Machine Faults – allows the end user to model a machine to understand frequencies. The ease of drag and drop technology enable the end user to create a virtual machine and view simulated frequencies, waveforms and spectrum.

SPECTRAL VISUALIZATION AND DEVELOPMENT, SVD INC.

SVD Inc. provides free online courses on their web site. The Canadian based company manufactures vibration analysis software and devices. The courses range from introductory maintenance philosophies to diagnostic methods. The only requirement for the end users is a web browser and Macromedia's Shockwave plug-ins (available as a free Internet download). Twelve courses are offered; four are described below:

- Introduction to Mechanical Vibrations — the basic concepts of mechanical vibrations are presented using a mass-spring-damper example of a vehicle suspension. End users gain an understanding of mechanical vibration, linear systems and system resonance while analyzing mechanical vibrations.

- Introduction to Machinery Signals – the end user is taught the basics of data acquisition, such as when and how to take measurements, aliasing and the alias foldover effect, and identifying time and stationary signals. Deterministic stationary signals and the processes that generate them are covered as well.

- Introduction to DSP (Data Signal Processing): Time and Frequency Domain – are two separate courses that are offered by SVD Inc. Data acquisition issues such as single channel and multi-channel analysis are taught along with unit of measurement. The concepts of mean, average and correlation, and how they relate to stationary signals are presented. The basic types of spectral plots and spectral analysis and their units of measurement are covered in frequency domain along with spectral estimators, parametric and non-parametric.

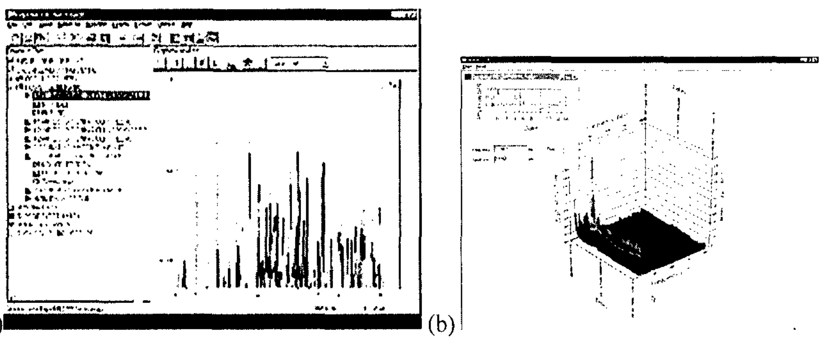

Figure 6 Vibration analysis software monitoring vibration signals for analysis, training and preventive maintenance: (a) ExpertALERT from Predict-DLI; (b) SpectraScope CAF from Spectral Visualization and Development, SVD Inc.

PREDICT-DLI

Predict DLI provides onsite training at their Cleveland or Seattle training center or customized training classes for companies interested in setting up their own onsite training classes. Predict DLI offers training in vibration analysis, lubricant analysis, thermography with digital imagery and visual inspections with digital imagery. The vibration curriculum currently consists of three courses described below:

- Vibration Analysis I and Machine Balancing – is a beginner's course for end users who have little or no experience in vibration data analysis. The course emphasizes vibration sources and measurement techniques as well as fundamental machine fault recognition. This course is designed for a practical focus on vibration analysis to detect major problems.

- Vibration Analysis II and Laser Alignment – this course is a follow-up to the basic course described up above. Here emphasis is placed on single channel analysis of vibration spectra. Problems found in gearboxes and belt driven machines are used for examples. Alignment tools and techniques are covered to include laser pre-alignment checks.

- Expert ALERT for Voyager – is designed for individuals who have purchased vibration analysis equipment from Predict DLI. Software commands and functions are discussed as well as analyzing, fine tuning data and manipulation of various plotting and display functions. Emphasis is placed on setting up the database and data collection communications and software interface.

CONCLUSIONS

This paper has partially reviewed previous work on vibration-based helicopter health and usage monitoring methods. Machinery failure prevention was shown to be an important component of the maintenance activity for most engineering systems, especially in aerospace. Due to specific continuous vibrations induced by the rotors, helicopters are particularly exposed to operations-induced fatigue damage, and their failure prevention increasingly relies on vibrations, health, and usage monitoring systems., helicopter vibration monitoring has evolved considerably over years, a special focus point being the signal analysis and interpretation algorithms. In recent years, new and more powerful signal processing methods have been developed. Three major directions have been identified and discussed in this paper:

a) Wavelet transform

b) Joint time-frequency Wigner-Ville distribution

c) Neural network and neuro-fuzzy

These vibration signal-processing methods have a generic origin, but their application to helicopter health-monitoring methodology is quite recent. These methods play an important role in early identification of incipient damage that can later develop in a potential threat to the system functionality, and even a flight accident. In aerospace applications, HUMS capabilities are to minimize aircraft operation cost, reduce maintenance flights, and increase flight safety.

Another important area identified in this paper is that of vibration-analysis education software. Several industries are currently utilizing predictive maintenance programs that utilize hardware and software capable of vibration-based diagnostic and prognostics. Though these capabilities have been developed for on-the-ground plants and equipment, the methodology adopted in their development could be transitioned to airborne equipment and helicopters. These predictive maintenance systems vendors offer vibration-analysis educational software that presents considerable opportunities.

The present study is neither final nor exhaustive. During the literature search, it was found that considerable effort is being currently invested in this field, far beyond the limited space available in this short paper. The authors are dedicated to continuing their search, revisiting the subject, and coming back with a new publication in continuation of our present efforts.

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FAILURE MODES AND ANALYSIS I

Chair: Ms. Debbie Aliya
Aliya Analytical