Current Issues in Vibration-Based Fault Diagnostics and Prognostics

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ABSTRACT

Current issues in vibration-based fault diagnostics and prognostics are: (a) fault/damage identification; (b) localization; and (c) monitoring. The fault/damage identification and localization are needed for diagnostics. The monitoring allows observing the fault/damage progression in time. Based on monitoring, the prognostics of the moment of failure, and hence of the remaining life could be performed. Critical in both the diagnostics and the prognostics is the existence of a reliable damage metric. Several methods for achieving this, from single parameter classification, through overall-statistics classification of the entire spectrum, to probabilistic neural network (PNN) method are presented. These methods are illustrated on: (i) simulated data; (ii) experimental data taken on simple-geometry calibration specimens; and (c) experimental data recorded on aging aircraft panels. The experimental data was obtained with the electro-mechanical (E/M) impedance technique using small and unobtrusive piezoelectric-wafer active sensors (PWAS) bonded to the structure. This experimental data was in the form of very high frequency (hundreds of kHz) spectrum representing the structural dynamics in sensor's neighborhood. The overall statistics approach, which is simplest to apply, could correctly classify near-field spectra using the dereverberated response and the correlation coefficient difference (CCD) damage metric, but it could not classify medium field spectra. The features-based PNN could correctly identify both medium-field and near-field data, but it requires more elaborate, two-stage, data processing that involves first features extraction and then classification.

Keywords: structural health monitoring, active sensors, vibrations, signal analysis; smart structures; piezoelectric, aging aircraft, cracks, damage, faults, diagnostics, prognostics, probabilistic neural networks, overall-statistics damage metrics.

1. INTRODUCTION

Vibration-based fault diagnostics and prognostics is an important component of structural health monitoring (SHM). Two aspects of vibration-based fault diagnostic and prognostics must be considered:

- (a) Vibrational interrogation of the structure, i.e., its excitation in a state of vibration and the capturing of the vibrational signal using conventional as well as novel sensors and actuators. This aspect is mainly a **hardware** issue. It requires the development of sensing and actuation methods suitable for adequate structural interrogation and signal capturing. In some cases, the excitation is built-in (e.g., rotating components, such as in turbomachinery and helicopters), while in other cases (e.g., fixed wing aircraft, bridges, etc.) it needs to be externally provided by an excitation source. Emerging active sensors are capable to be both exciters and receptors of vibration signals, in the high kHz range.
- (b) Processing of the vibrational signal for the extraction of diagnostic information and performance of prognostics. Here, the emphasis is on **software**. Irrespective of their origin and frequency band, the vibrational signals need to be processed such that a clear differentiation between pristine and damaged states can be found.

Current issues in vibration-based fault diagnostics and prognostics are related to: (i) fault/damage identification; (ii) fault/damage localization; and (iii) fault/damage monitoring. The fault/damage identification and localization are needed to perform the diagnostics. The monitoring allows observing the fault/damage progression in time. Based on the time progression, prognostics of the moment of failure, and hence of the remaining life can be performed. Critical in both the diagnostics and the prognostics is the existence of a reliable damage metric. Currently, many digital signal-processing techniques are being developed and applied to fault detection and machine-health diagnosis. The signal processing methods for machine-health diagnosis can be classified into time-domain analysis, frequency domain analysis, and joint time-frequency analysis. This paper will focus on frequency domain analysis, and will critically compare several methods for processing spectral signatures. These methods vary from single parameter classification, through overall-statistics classification of the entire spectrum, to probabilistic neural network method applied in conjunction with feature extraction algorithms. Key to such signal processing are several issues: (i) identification of signal features that adequately represent the "pristine" and "damaged" conditions; (ii) development of a damage metric, that is able to express, in a simple scalar number, the condition of the structure and if damage is present or not. Fritzen and Bohle (1999) showed that structural damage, such as fatigue cracks in metals or delamination of layer composite structures, causes characteristic local changes of stiffness, damping, and/or mass. Thus, shifts of the dynamic characteristics (frequencies, modeshapes, modal damping) occur. The

deviation between the ‘pristine’ dynamic properties and the ‘damaged’ dynamic properties can be used to detect damage, and diagnose its location and extend. Morita et al (2001) used a damage-frequency correlation matrix trained on the first 5 structural frequencies of a five story steel frame to identify damage presence and location from changes in frequencies and modeshapes. Farar et al. (2001) listed the implementation issues for an integrated structural health monitoring system: (a) hardware implementation of an active micro electromechanical system consisting of excitation, sensors, microprocessor, and wireless modem integrated pack; and (b) signal processing to identify damage. The latter involves a feature-extraction data-compression process, which identifies damage-sensitive properties from the measured vibration response. Data compression into small-size feature-vectors is necessary to keep the problem size within manageable limits. In addition, realistic damage scenarios are always accompanied by nonlinear and/or nonstationary structural response, for which adequate analysis methods are required.

2. SINGLE-PARAMETER CRACK-DAMAGE DETECTION USING SHORT TIME FOURIER TRANSFORM AND WIGNER-VILLE DISTRIBUTION

Single-parameter classification is the simplest approach to damage detection. Since the time response of a cracked component is inherently nonlinear, advanced signal processing methods need to be used. In the following example, the signal is analyzed using Short Time Fourier Transform (STFT) and Wigner-Ville distribution (WVD).

2.1 Dynamic Model of a Cracked Component

The basis for using the forced oscillation method for the fatigue crack diagnostics lies in the fact that in a cracked component the stiffness is nonlinear and the nonlinearity level changes with the crack size. Assuming that the component under analysis can be approximated with a single degree of freedom nonlinear oscillator, the equations of motion can be expressed in non-dimensional form as follows (Gelman et al., 2001):

$$\begin{cases} \ddot{X} + 2\zeta_s \omega_s \dot{X} + \omega_s X = A \sin(\omega t + \varphi), & X \geq 0 \\ \ddot{X} + 2\zeta_c \omega_c \dot{X} + \omega_c X = A \sin(\omega t + \varphi), & X < 0 \end{cases} \quad (1)$$

where the subscripts *C* and *S* signify “compression” and “stretching” of the crack. Equation (1) is a piecewise-linear nonlinear equation. At compression, the crack is closed and the material behaves like a continuum; hence, the compression stiffness is the same as that of the material without crack. By the same argument, $\omega_c = \omega_n$, where ω_n is the natural frequency of the component in pristine condition. At stretching, the crack opens, the material becomes discontinuous, and the effective stiffness decreases. Hence, $\omega_s < \omega_n$. The relationship between ω_s and the crack size depends on the loading type and crack position (Figure 1). The simplest case, which is sufficient to illustrate the general damage detection approach, is to assume $\omega_s = \omega_n \sqrt{1-r}$, $\omega_c = \omega_n$, where r is the relative crack size, $r = a/h$. The variables ω and φ are the constant excitation frequency and the random initial phase, respectively. The random initial phase is uniformly distributed in the interval $[0, 2\pi]$.

Figure 1 Stretching and compression effects in a cracked component. In stretching crack is opening and in compression crack is closing: (a) axial loading; (b) bending

2.2 Damage detection strategy

Crack presence in the structure modifies (decreases) the effective stiffness and hence the main frequency. In addition, the nonlinear character of the equations leads to parametric resonances, which appear as additional features in the frequency spectrum (Figure 2a). The stiffness and the nonlinearities also change with the crack size. In our investigation, we tracked the main frequency changes for increasing relative crack size ($r = 0, 0.1, 0.4, 0.6$), corresponding to four damage cases: pristine case ($r = 0$), small damage ($r = 0.1$), medium damage ($r = 0.4$), and severe damage ($r = 0.6$). For each relative crack size, the nonlinear time-response signal was generated using MATLAB SIMULINK numerical solution of Equation (1), as shown in Figure 2b. The natural frequency of the component without crack was $f_n = 20 \text{ Hz}$ ($\omega_n = 40\pi \text{ rad/s}$) while the damping coefficients for stretching and compression were $\zeta_s \omega_s = \zeta_c \omega_c = 10 \text{ rad/s}$. The frequency of the signal changes as the crack progresses. The frequency domain analysis calculated the power spectral density (PSD) using two methods: (a) Short Time Fourier Transform (STFT); and (b) Wigner-Ville distribution. Then, the peaks in the frequency spectrum were observed. Changes in the amplitude and the frequency of the main resonance, and apparition of higher harmonics in the frequency spectrum were noticed. To classify the outcome of the two methods, a statistical approach was employed (Fisher criterion). To simulate the statistical variability of the signal, a Monte Carlo outer loop was applied on the algorithm. For each crack size, the simulation was run 1000 times, each time with a different randomly selected initial phase, ϕ . The results obtained at each damage level were compared with the pristine results using Fisher's linear discriminant (Fisher criterion), expressed as:

$$F = (m_2 - m_1)^2 / (s_1^2 + s_2^2) \quad (2)$$

where m_1 and m_2 are the projected means, while s_1 and s_2 are the standard deviations of the two populations that are being compared. Here, the populations are the values of the main frequency in the “damaged” and “pristine” cases.

Figure 2 (a) Additional features present in the spectrum; (b) flowchart diagram of the simulation strategy

Figure 3 STFT and WVD comparison for the severe damage case, $r = 0.6$: (a) STFT; (b) WVD

2.3 Results and Diagnostic Effectiveness

In the pristine case ($r = 0$), both VWD and STFT gave same result, a main resonance peak at 20 Hz. As the relative crack size increased, additional spectral features appeared. Figure 3a shows the additional features present in the STFT spectrum. As anticipated, the 1st and 2nd higher harmonics of the main frequency appear ($f_2 \cong 35$ Hz, $f_3 \cong 53$ Hz). Figure 3b shows the additional features present in the WVD spectrum. The 1st and 2nd half-tone interferences, ($f_{1/2} \cong 9$ Hz, $f_{3/2} \cong 26$ Hz) as well as the 1st higher harmonic of the main frequency ($f_2 \cong 35$ Hz) are noticeable. It was noticed that the amplitude of the harmonics grew nonlinearly with the relative crack size. At small crack size ($r = 0.1$), the first higher harmonic appeared only in the STFT, while WVD showed some subharmonic artifacts. At higher relative crack size ($r = 0.4$), STFT displayed two higher harmonics ($f_2 \cong 35$ Hz, $f_3 \cong 53$ Hz), while WVD presented the 1/2 and 3/2 interference sub-harmonics ($f_{1/2} \cong 9$ Hz, $f_{3/2} \cong 26$ Hz). The Fisher criterion was used to compare the detection effectiveness of the two signal analysis methods, STFT and WVD. The Fisher criterion was calculated for pairs of classes representing the amplitudes of the main harmonic for the pristine case and the various damage cases (Table 1). The change in the criterion as the damage progresses was examined. Table 2 and Figure 5 show that the WVD analysis has much stronger damage detection capability than STFT. In conclusion, both WVD and STFT methods predict the presence of the damage. The STFT method gives a better indication of the higher harmonics of the main frequency due to the crack growth. On the other hand, WVD method gives stronger sensitivity to the crack presence based on the changes in the main frequency. This latter observation has also been substantiated by statistical analysis using Fisher criterion. Further details of these findings can be found in Cuc (2002).

Table 1 Main frequency and its standard dev.

	r	0	0.1	0.4	0.6
STFT	A_{STFT} , dB	48.6	48.8	57.2	43.5
	St-dev, %	0.2%	0.1%	0.2%	0.1%
WVD	A_{WVD} , dB	17.5	21.8	26.0	11.8
	St-dev, %	1.1%	0.3%	0.2%	0.4%

Table 2 Fisher criterion values with STFT and WVD analysis.

Method	Fisher criterion value		
	Pristine vs. small damage	Pristine vs. medium damage	Pristine vs. large damage
STFT	0.001	1.476	4.119
WVD	0.666	3.297	43.367

Figure 4 Damage detection effectiveness of STFT vs. WVD

3. SPECTRUM CLASSIFICATION

The example presented in the previous section used one spectral parameter alone, the amplitude of the main resonance, to achieve classification. However, actual structures present a rich spectrum that has many resonance frequencies. This is especially true when high-frequency spectra in the hundred of kHz are used for the identification of incipient damage, such as in the active sensor electromechanical (E/M) impedance technique (Liang *et al.*, 1994; Sun *et al.*, 1994; Giurgiutiu and Rogers, 1998; Lopes *et al.*, 1999; Park *et al.*, 2000; Giurgiutiu *et al.*, 2002). The use of high frequencies ensures that the damage metric detects incipient damage at an early stage. Two approaches have emerged for the classification of an entire spectrum: (a) overall-statistics methods, and (b) features-based methods. Both approaches are illustrated here, in the context of statistically controlled calibration experiments performed on circular plate specimens with various amounts of damage. The featureless approach is simpler, since one attempts to directly compare the strings of numbers associated with each spectrum. Such a flat consideration may lead to a large-dimensional problem, and the associate computational difficulty. However, its detection capabilities may not be as good as those of features-based methods.

3.1 Calibration Experiments on Circular Plates

Typical E/M impedance data takes the form of frequency domain plots of the E/M impedance real part, which accurately represents the local structural impedance at the sensor location (Giurgiutiu and Zagari, 2001). An Impedance Analyzer (e.g., HP 4194A), which performs impedance measurements with 401 data points along the frequency axis, is utilized. The advantage of the E/M impedance method is its high frequency capability. Thus, it can measure with ease the high order harmonics, which are more sensitive to local damage than the low order harmonics. During data collection over a high frequency band, the investigator should carefully consider the size of frequency interval to ensure good resolution of the measurements. Poor resolution of the spectrum may hide important harmonics. A controlled active-sensor structural health

monitoring experiments was conducted to generate consistent benchmark test data for damage metrics development and calibration. Five statistical groups of specimens with increasing amount of damage were tested. Each group contained five 1.6 mm thick 2024-T3 aluminum alloy 100 mm diameter identical plates. A 7-mm diameter, 0.2-mm thick piezoelectric-wafer active sensor (PWAS) was placed in the center. A 10-mm simulated crack was produced in each specimen in the form of a narrow slit cut with the electric discharge machining (EDM) process. The crack was incrementally brought closer to the plate center (Table 4, column 1). Each crack position represented a different state of damage. Group 0 represented the *pristine* condition. The amount of damage increased as the group number increased. Within each group, the damage was identically replicated to all the group members. Thus, the method's repeatability and reproducibility was tested. High-frequency structural impedance readings were taken in three frequency bands: 10-40 kHz; 10-150 kHz; and 300-450 kHz. The 10-40 kHz frequency band, which has fewer modes, is shown in column 2 of Table 4. It is appreciated that, as damage progresses, two phenomena happen: (a) the resonance frequencies change; and (b) new resonance frequencies appear. Similar results were also obtained for the other two frequency bands. The third column of Table 4 gives the values of the six most prominent resonance frequencies of each spectrum. Later in this section, these frequencies will be used as input data to a probabilistic neural network (PNN) classification algorithm.

3.2 Overall-Statistics Classification

To date, several overall-statistics damage metrics have been proposed for comparing impedance spectra and assess the damage presence. Among them, the most popular are: the root mean square deviation (RMSD), the mean absolute percentage deviation (MAPD), and the correlation coefficient difference (CCD):

$$RMSD = \sqrt{\sum_N [\text{Re}(Z_i) - \text{Re}(Z_i^0)]^2 / \sum_N [\text{Re}(Z_i^0)]^2}, \quad (3)$$

$$MAPD = \sum_N \left| [\text{Re}(Z_i) - \text{Re}(Z_i^0)] / \text{Re}(Z_i^0) \right| \quad (4)$$

$$CCD = 1 - CC, \quad \text{where } CC = \frac{1}{\sigma_Z \sigma_{Z^0}} \sum_N [\text{Re}(Z_i) - \text{Re}(\bar{Z})] \cdot [\text{Re}(Z_i^0) - \text{Re}(\bar{Z}^0)], \quad (5)$$

where N is the number of sample points in the spectrum (here, $N = 401$), and the superscript 0 signifies the pristine (baseline) state of the structure. Z , Z^0 are the mean values, while σ_Z , σ_{Z^0} are the standard deviations. Equations (6.1)-(6.4) result in a scalar number, which represent the relationship between the compared spectra. Thus, we expect that the variations in $\text{Re}(Z)$ and the appearance of new harmonics may alter the scalar value of damage index identifying the damage. The advantage of using Equations (3), (4), (5) is that the input impedance spectrum does not need any pre-processing, i.e., the data obtained from measurement equipment can be directly used to calculate the damage index.

Table 3 presents the results for the three overall-statistic damage metrics considered here. It was found that the choice of frequency band plays significant role. Although it was expected that the damage metric would increase as the damage becomes more severe, the variation of these metrics with damage intensity in the 10-40 kHz and 10-150 kHz frequency bands was not uniform. However, in the 300-450 kHz frequency band, the situation was much better. It was found that the correlation coefficient difference raised to the power seven (CCD^7) tends to linearly decrease with the radial position of the crack (Figure 5). This indicates that CCD^7 could be a valuable overall-statistics damage metric for identifying damage, and locating its position.

Table 3 Overall-statistics damage metrics for various frequency bands

Frequency band	11-40 kHz				11-150 kHz				300-450 kHz			
Compared groups	0_1	0_2	0_3	0_4	0_1	0_2	0_3	0_4	0_1	0_2	0_3	0_4
RMSD, %	122	116	94	108	144	161	109	118	93	96	102	107
MAPD, %	107	89	102	180	241	259	170	183	189	115	142	242
CCD, %	84	75	53	100	93	91	52	96	81	85	87	89

Figure 5 Monotonic variation of the CCD^7 damage metric with the crack radial position on a 50-mm radius plate in the 300—450 kHz band

Table 4 Calibration experiments on circular plates

<p>Group 0 (pristine). 5 Plates with no cracks</p>	<p>Plate 0-1</p>	<table><tr><th>#</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr><tr><td></td><td>Plate 0-1</td><td>Plate 0-2</td><td>Plate 0-3</td><td>Plate 0-4</td><td>Plate 0-5</td></tr><tr><td>Frequency, Hz</td><td>f_1</td><td>12885</td><td>12740</td><td>13030</td><td>12885</td><td>12740</td></tr><tr><td></td><td>f_2</td><td>16220</td><td>16075</td><td>16510</td><td>16148</td><td>16148</td></tr><tr><td></td><td>f_3</td><td>20135</td><td>19918</td><td>20425</td><td>20135</td><td>19918</td></tr><tr><td></td><td>f_4</td><td>24195</td><td>23978</td><td>24630</td><td>24413</td><td>24050</td></tr><tr><td></td><td>f_5</td><td>28980</td><td>28618</td><td>29343</td><td>28980</td><td>28618</td></tr><tr><td></td><td>f_6</td><td>39058</td><td>38913</td><td>39493</td><td>39493</td><td>38913</td></tr></table>	#	1	2	3	4	5		Plate 0-1	Plate 0-2	Plate 0-3	Plate 0-4	Plate 0-5	Frequency, Hz	f_1	12885	12740	13030	12885	12740		f_2	16220	16075	16510	16148	16148		f_3	20135	19918	20425	20135	19918		f_4	24195	23978	24630	24413	24050		f_5	28980	28618	29343	28980	28618		f_6	39058	38913	39493	39493	38913
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<p>Group 1 (slight damage) 5 plates with crack at 40mm</p>	<p>Plate 1-1</p>	<table><tr><th>#</th><th>6</th><th>7</th><th>8</th><th>9</th><th>10</th></tr><tr><td></td><td>Plate 1-1</td><td>Plate 1-2</td><td>Plate 1-3</td><td>Plate 1-4</td><td>Plate 1-5</td></tr><tr><td>Frequency, Hz</td><td>f_1</td><td>12958</td><td>12813</td><td>12813</td><td>12813</td><td>12813</td></tr><tr><td></td><td>f_2</td><td>19700</td><td>19555</td><td>19555</td><td>19483</td><td>19483</td></tr><tr><td></td><td>f_3</td><td>20353</td><td>20135</td><td>20063</td><td>20063</td><td>20063</td></tr><tr><td></td><td>f_4</td><td>28400</td><td>28183</td><td>28183</td><td>28183</td><td>28183</td></tr><tr><td></td><td>f_5</td><td>29270</td><td>28980</td><td>28835</td><td>28908</td><td>28835</td></tr><tr><td></td><td>f_6</td><td>39638</td><td>39203</td><td>39203</td><td>39203</td><td>39130</td></tr></table>	#	6	7	8	9	10		Plate 1-1	Plate 1-2	Plate 1-3	Plate 1-4	Plate 1-5	Frequency, Hz	f_1	12958	12813	12813	12813	12813		f_2	19700	19555	19555	19483	19483		f_3	20353	20135	20063	20063	20063		f_4	28400	28183	28183	28183	28183		f_5	29270	28980	28835	28908	28835		f_6	39638	39203	39203	39203	39130
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<p>Group 2 (intermediate damage I) 5 plates with crack at 25mm</p>	<p>Plate 2-1</p>	<table><tr><th>#</th><th>11</th><th>12</th><th>13</th><th>14</th><th>15</th></tr><tr><td></td><td>Plate 2-1</td><td>Plate 2-2</td><td>Plate 2-3</td><td>Plate 2-4</td><td>Plate 2-5</td></tr><tr><td>Frequency, Hz</td><td>f_1</td><td>12450</td><td>12450</td><td>12523</td><td>12450</td><td>12523</td></tr><tr><td></td><td>f_2</td><td>12885</td><td>12885</td><td>13030</td><td>12958</td><td>12958</td></tr><tr><td></td><td>f_3</td><td>20280</td><td>20135</td><td>20353</td><td>20208</td><td>20353</td></tr><tr><td></td><td>f_4</td><td>27965</td><td>27893</td><td>28038</td><td>27893</td><td>27965</td></tr><tr><td></td><td>f_5</td><td>29270</td><td>28980</td><td>29343</td><td>29198</td><td>29198</td></tr><tr><td></td><td>f_6</td><td>39565</td><td>39348</td><td>39783</td><td>39348</td><td>39710</td></tr></table>	#	11	12	13	14	15		Plate 2-1	Plate 2-2	Plate 2-3	Plate 2-4	Plate 2-5	Frequency, Hz	f_1	12450	12450	12523	12450	12523		f_2	12885	12885	13030	12958	12958		f_3	20280	20135	20353	20208	20353		f_4	27965	27893	28038	27893	27965		f_5	29270	28980	29343	29198	29198		f_6	39565	39348	39783	39348	39710
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<p>Group 3 (intermediate damage II) 5 plates with crack at 10mm</p>	<p>Plate 3-1</p>	<table><tr><th>#</th><th>16</th><th>17</th><th>18</th><th>19</th><th>20</th></tr><tr><td></td><td>Plate 3-1</td><td>Plate 3-2</td><td>Plate 3-3</td><td>Plate 3-4</td><td>Plate 3-5</td></tr><tr><td>Frequency, Hz</td><td>f_1</td><td>12305</td><td>12160</td><td>12233</td><td>12233</td><td>12160</td></tr><tr><td></td><td>f_2</td><td>12885</td><td>12813</td><td>12885</td><td>12958</td><td>12740</td></tr><tr><td></td><td>f_3</td><td>20208</td><td>19990</td><td>20135</td><td>20135</td><td>19990</td></tr><tr><td></td><td>f_4</td><td>23325</td><td>23108</td><td>23325</td><td>23253</td><td>23108</td></tr><tr><td></td><td>f_5</td><td>29198</td><td>28908</td><td>29053</td><td>28980</td><td>28835</td></tr><tr><td></td><td>f_6</td><td>39638</td><td>39348</td><td>39565</td><td>39493</td><td>39203</td></tr></table>	#	16	17	18	19	20		Plate 3-1	Plate 3-2	Plate 3-3	Plate 3-4	Plate 3-5	Frequency, Hz	f_1	12305	12160	12233	12233	12160		f_2	12885	12813	12885	12958	12740		f_3	20208	19990	20135	20135	19990		f_4	23325	23108	23325	23253	23108		f_5	29198	28908	29053	28980	28835		f_6	39638	39348	39565	39493	39203
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	f_6	39638	39348	39565	39493	39203																																																		
<p>Group 4 (strong damage) 5 plates with crack at 3mm</p>	<p>Plate 4-1</p>	<table><tr><th>#</th><th>21</th><th>22</th><th>23</th><th>24</th><th>25</th></tr><tr><td></td><td>Plate 4-1</td><td>Plate 4-2</td><td>Plate 4-3</td><td>Plate 4-4</td><td>Plate 4-5</td></tr><tr><td>Frequency, Hz</td><td>f_1</td><td>11580</td><td>11653</td><td>11435</td><td>11580</td><td>11435</td></tr><tr><td></td><td>f_2</td><td>12740</td><td>12740</td><td>12668</td><td>12740</td><td>12595</td></tr><tr><td></td><td>f_3</td><td>15278</td><td>15350</td><td>15060</td><td>15278</td><td>15133</td></tr><tr><td></td><td>f_4</td><td>17380</td><td>17380</td><td>17090</td><td>17235</td><td>17163</td></tr><tr><td></td><td>f_5</td><td>22093</td><td>22093</td><td>21658</td><td>22165</td><td>21803</td></tr><tr><td></td><td>f_6</td><td>38623</td><td>38550</td><td>38188</td><td>38550</td><td>37970</td></tr></table>	#	21	22	23	24	25		Plate 4-1	Plate 4-2	Plate 4-3	Plate 4-4	Plate 4-5	Frequency, Hz	f_1	11580	11653	11435	11580	11435		f_2	12740	12740	12668	12740	12595		f_3	15278	15350	15060	15278	15133		f_4	17380	17380	17090	17235	17163		f_5	22093	22093	21658	22165	21803		f_6	38623	38550	38188	38550	37970
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	f_3	15278	15350	15060	15278	15133																																																		
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	f_5	22093	22093	21658	22165	21803																																																		
	f_6	38623	38550	38188	38550	37970																																																		

3.3 Features-Based PNN Classification

Features extraction reduces the problem dimensionality and separates essential information from non-essential information. In spectral analysis, the features-vector approach recognizes that the number and characteristics of resonance peaks play a major role in describing the dynamic behavior of the structure. By considering the essential features of the spectrum, i.e. the peaks at resonance frequencies, meaningful information corresponding to the particular state of structural health can be extracted. This information can be organized in a features vector, where each feature corresponds to a certain resonance frequency. As an illustration, consider the E/M impedance spectra reproduced in Table 4b. Each spectrum contains 401 data points positioned at 0.075 kHz intervals in the 10 to 40 kHz band. Five spectra are presented: one pristine and four with various degrees of damaged. Although the difference between spectra is obvious, quantification of this difference is neither obvious nor immediate. Using the features vector approach, it is possible to distinguish between a “pristine” and a “damaged” structure by considering the number and the position of the resonance peaks. For example, the pristine-plate spectrum of Table 4b displays four dominant resonance peaks (12.8, 20.1, 28.9, and 39.2 kHz), and several minor peaks (16.2, 24.2, 34.1, 36.35 kHz). By considering these features, the dimensionality of the problem can be reduced by almost 2 orders of magnitude, from 400-points to less than 10 features. The details for these feature vectors are given in Table 4c. For the ‘strong damage’ plate (Table 4, row 5), we distinguish six dominant peaks (11.6, 12.7, 15.2, 17.4, 22.0, 38.6 kHz). Though the number of features has increased, the problem size is still one order of magnitude less than in a featureless approach. Similar results were also observed in the 10-150 kHz and 300-450 kHz bands.

Once the feature vectors are established, the classification problem can be approached in the features space. Several features-based classification algorithms have been proposed, based on statistical methods and on neural networks. We explored a probabilistic neural network (PNN) classification algorithm.

The results of our tests are given in Tables 5 and 6. Table 5 shows the PNN classification performed with a 4-frequency features vector. The 4 frequencies used in the features vector were the main resonance frequencies of Table 4c. The results of Table 5 indicate that good classification was attained for Groups 2, 3, 4, but not for Group 1. Group 1 (slight damage) was misclassified with Group 0 (pristine). This misclassification problem could not be fixed by increasing the number of training vectors (Tests II, III, and IV in Table 5). However, when the size of the features vectors was increased from four to six, the classification improved dramatically. With only one vector used for training in each group, the PNN consistently predicted the right results. Thus, clear distinction could be

Table 5 Synoptic classification table for circular plates using 4-frequency feature vectors

		Group 0 (no damage)					Group 1 (r=40 mm)					Group 2 (r=25 mm)					Group 3 (r=10 mm)					Group 4 (r=3 mm)					
Plate #		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
Test #	I	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	IN
		-	0	1	1	0	-	1	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	OUT
	II	T	T	V	V	V	T	T	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	IN
		-	-	1	1	0	-	-	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	OUT
	III	T	T	T	V	V	T	T	1	1	1	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	IN
		-	-	-	1	0	-	-	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	OUT
	IV	T	T	T	V	T	T	T	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	IN
		-	-	-	1	-	-	-	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	OUT

Table 6 Synoptic classification table for circular plates using 6-frequency feature vectors

		Group 0 (no damage)					Group 1 (r=40 mm)					Group 2 (r=25 mm)					Group 3 (r=10 mm)					Group 4 (r=3 mm)					
Plate #		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
Test #	I	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	IN
		-	0	0	0	0	-	1	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	OUT
	II	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	IN
		0	-	0	0	0	1	-	1	1	1	2	-	2	2	2	3	-	3	3	3	4	-	4	4	4	OUT
	III	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	T	V	V	V	V	T	V	V	V	IN
		0	0	-	0	0	1	1	-	1	1	2	2	-	2	2	3	3	-	3	3	4	4	-	4	4	OUT
	IV	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	IN
		0	0	0	-	0	1	1	1	-	1	2	2	2	-	2	3	3	3	-	3	4	4	4	-	4	OUT
	V	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	V	V	V	V	T	IN
		0	0	0	0	-	1	1	1	1	-	2	2	2	2	-	3	3	3	3	-	4	4	4	4	-	OUT

Legend: T = training vector; V = validation vector;

IN = input to PNN, OUT = output from PNN

established between the spectra generated by the ‘pristine’ case (Group 0) and the ‘damage’ cases (Groups 1, 2, 3, 4). In addition, clear distinction could also be determined between the spectra of various ‘damage’ groups that correspond to various crack positions (Group 4, 3, 2, 1 correspond to $r = 3, 10, 25, 40$ mm, respectively). These examples have shown that PNN approach, in conjunction with a sufficiently-large features vector, can successfully identify the damage presence and its location. Further details of this work can be found in Zagari (2002), and Zagari and Giurgiutiu (2002).

4. CLASSIFICATION EXPERIMENTS ON AGING AIRCRAFT PANELS

The circular-plates calibration experiments discussed in the previous section have shown that overall statistics and probabilistic neural networks (PNN) can be used to classify damage of various degrees in simple-geometry specimens. In the present section, we show how the same approaches can be used to classify damage in realistic aircraft panels. In these experiments, we used two aircraft panels, one pristine (Panel 0), and the other with simulated cracks originating from rivet holes (Panel 1). The panels present typical structural features (rivets, splices, stiffeners, etc.), which complicate their structural dynamics. The objective of the experiment was to detect a 19 mm crack originating from a rivet hole (Figure 7). The panels were instrumented with eight piezoelectric wafer active sensors (PWAS), four on each panel: two sensors were placed in the *medium field* (100 mm from the crack location), and two in the *near field* (10 mm from the crack location). The location of the sensors was identical on both panels. The sensor labels are given in Table 7. It is anticipated that sensors placed next to a similar configuration of structural features (rivets, stiffeners, etc.) will give similar E/M impedance spectra. It was also anticipated that the presence of damage would change the sensors readings. Thus, in the medium field (Figure 6), the sensors S1, S2, S3 are in pristine zones, and should give similar readings, while S4 is in a damaged zone, and should give a different reading. Similarly, in the near field, S5, S6, S7 are ‘pristine’, while S8 is ‘damage’. E/M impedance spectrum was collected for each sensor in the 200-550 kHz frequency band.

Table 7 Position on sensors on aircraft panels

	Panel 0		Panel 1	
	Pristine	Pristine	Pristine	Crack
Medium field	S1	S2	S3	S4
Near field	S5	S6	S7	S8

(a)

(b)

Figure 6 (a) Schematics of the Panel 1 specimen and location of PWAS # S3, S4, S7, S8; (b) photograph of the aging aircraft panel 1 with PWAS installed on its surface. Panel 0, containing S1, S2, S5, S6, is identical, but does not have cracks

4.1 Overall-Statistics Classification of Crack Damage in Aircraft Panels

Figure 7a presents the superposed spectra for the near-field PWAS. It is apparent that the ‘pristine’ PWAS (S5, S6, S7) have very similar spectra, while the ‘damage’ PWAS (S8) has a markedly different spectrum, with an elevated high-density cluster of peaks at in the 400-450 kHz range. To quantify this situation, we used the dereverberated response (DR). Figure 7b shows the DR’s extracted from the Figure 7a spectra. It is apparent that the ‘pristine’ DR’s are very similar, while the ‘damage’ DR is distinctly different. The DR’s were processed with a set of overall-statistics metrics: RMSD, MAPD, CCD, as given by Equations (2), (3), (4), respectively. The classification results are given in Table 8. “Pristine vs. pristine” and “damage vs. pristine” values of the classification metrics were calculated. For good classification, the pristine-pristine values should be relatively small, while the damage-pristine values should be relatively large. Examination of Table 8 reveals that this criterion is best met by the CCD metric. The same message is also conveyed by Figure 9, which shows that CCD has detection sensitivity at least 6 time stronger than RMSD and MAPD.

Figure 7 Superposition of PWAS near field E/M impedance spectra in the 200-550 kHz band; (b) dereverberated response

Figure 8 Average relative response of RSMD, MAPD, and CCD metrics for near field damage measurements

Table 8 Response of RMSD, MAPD, and CCD metrics to near field damage (S5, S6, S7 = pristine, S8 = damage)

Class	Pristine vs. Pristine			Damaged vs. Pristine		
	S5_S6	S5_S7	S6_S7	S5_S8	S6_S8	S7_S8
RMSD	4.09%	8.74%	5.71%	15.64%	14.10%	10.10%
	6.18%			13.28		
MAPD	3.75%	8.43%	5.88%	13.26%	11.89%	8.05%
	6.02%			11.07%		
CCD	0.94%	0.63%	0.07%	5.70%	7.45%	6.77%
	0.55%			6.64%		

4.2 Features-Based PNN Classification of Crack Damage in Aircraft Panels

Previous section has shown that overall-statistics damage metrics could successfully classify the dereverberated response extracted from near-field spectra. However, when the same approach was tried on the medium-field spectra, the results were less conclusive. The reason for this lies in the nature of the medium-field spectra, which are inherently different from the near-field spectra. As shown in Figure 9a, the presence of damage does not modify the dereverberated response of medium-field spectra as it did in the near-field spectra. For the medium-field spectra, the presence of damage produces a marked changed in the number, position, and amplitude of resonance peaks. Based on these observations, it became apparent that for

medium-field spectra a features-vector classification would be more appropriate. Figure 9b presents the result of processing the S1 spectrum with an automatic features-extraction algorithm, showing the 48 resonance frequencies identified by this process. Similar results were obtained for the other spectra (Zagrai and Giurgiutiu, 2002). The resulting features-vectors were used as input to the PNN classification algorithm.

The results of the PNN classification are presented in Table 9. Three tests were performed. In each test, one ‘pristine’ vector was used for training, and then the remaining three vectors were used for validation. Dichotomous classification was used: an outcome of 1 signifies that the vector presented during the validation was in the same class with the vector used during training, while an outcome of 0 signifies the opposite. Thus, all the vectors that return an outcome of 1 could be considered to represent ‘pristine’ conditions, while those that returned an outcome of 0 represented ‘damage’ conditions. For example, in Test I, vector S1 was used for testing, while S2, S3, S4 were used for validation. The outcomes on S2 and S3 were 1, i.e., S2 and S3 belong in the same class with S1, i.e., ‘pristine’. The outcome for S4 was 0, i.e., S4 does not belong in the same class with S1, i.e., it does not represent a ‘pristine’ condition, hence it represents a ‘damaged’ condition. Table 9 indicates that all the three tests performed gave perfect results, i.e., the ‘pristine’ situations (S1, S2, S3) and the ‘damage’ situation were correctly classified irrespective of the training vector choice. After the successful classification of the medium-field data, the same PNN approach was also successfully used to perform the classification of the near-field data (second part of Table 9). Further details of this work can be found in Zagrai (2002), and Zagrai and Giurgiutiu (2002).

Table 9 Synoptic classification table for PWAS medium field and near field using 48-frequencies features vectors and probabilistic neural networks

		Medium Field				Near Field				
Vector		S1	S2	S3	S4	S5	S6	S7	S8	
Test	I	T	V	V	V	T	V	V	V	IN
		–	1	1	0	–	1	1	0	OUT
	II	V	T	V	V	V	T	V	V	IN
		1	–	1	0	1	–	1	0	OUT
	III	V	V	T	V	V	V	T	V	IN
		1	1	–	0	1	1	–	0	OUT

Legend: T = training, V = validation

Figure 9 Aircraft-panel damage detection in PWAS medium field: (a) superposition of E/M impedance spectra for PWAS S1, S2, S3, S4; (b) automatic features extraction: 48 resonance frequencies identified in the spectrum of PWAS S1

5. SUMMARY AND CONCLUSIONS

Current issues in vibration-based fault diagnostics and prognostics are: (a) fault/damage identification; (b) localization; and (c) monitoring. The fault/damage identification and localization are needed to perform the diagnostics. The monitoring allows observing the fault/damage progression in time. Based on this time progression, prognostics of the moment of failure, and hence of the remaining life can be performed. Critical in both the diagnostics and the prognostics is the existence of a reliable damage metric. This paper has presented and critically compared several methods for achieving this, from single parameter classification, through overall-statistics classification of the entire spectrum, to probabilistic neural network

method applied in conjunction with feature extraction algorithm. These methods are illustrated on: (i) simulated data; (ii) experimental data taken on simple-geometry calibration specimens; and (c) experimental data obtained on aging aircraft panels.

Single-parameter classification was illustrated on the simulated non-linear forced response signal of cracked component. The Short Time Fourier Transform (STFT) and Wigner-Ville distribution (WVD) were used to analyze the signal, while the Fisher criterion was used for classification. Both WVD and STFT methods predict the presence of the damage. The STFT method gave a better indication of the higher harmonics appearing due to the crack growth. On the other hand, WVD method gives stronger sensitivity of the main frequency to the crack presence based on the changes in the main frequency, as substantiated by the statistical analysis using Fisher criterion.

Classification of entire spectra was illustrated on experimental data obtained from two types of specimens: (i) 25 simple geometry circular plates with various amounts of damage; and (ii) two aging aircraft panels, one pristine (Panel 0), and the other with simulated cracks originating from rivet holes (Panel 1). The experimental data was recorded with the electro-mechanical (E/M) impedance technique using small and unobtrusive piezoelectric-wafer active sensors (PWAS) bonded to the structure. The recorded experimental data came in the form of very high frequency (hundreds of kHz) spectra representing the structural dynamics in sensor's neighborhood.

For spectral classification, two approaches were used: (a) overall-statistics metrics; and (b) features-vector probabilistic neural network. The advantage of using overall-statistics damage metrics is that the input impedance spectrum does not need any pre-processing, i.e., the data obtained from measurement equipment can be directly used to calculate the damage metric. The overall statistics used in this investigation were: the root mean square deviation (RMSD), the mean absolute percentage deviation (MAPD), and the correlation coefficient difference (CCD). In the circular plates experiments, it was found that, in the 300-450 kHz frequency band, the correlation coefficient difference raised to the power seven (CCD^7), which tends to linearly decrease with the radial position of the crack, could be a valuable overall-statistics damage metric for identifying damage, and locating its position. In the aging aircraft panels experiment, the overall statistics metrics could only be successfully applied to the identification of near-field damage. In this case, the CCD metric applied to the dereverberated spectral response was shown to be 6 times more sensitive than the RMSD and MAPD metrics.

The probabilistic neural network (PNN) approach was found to be very successful when applied in conjunction with a features-extraction algorithm. The use of features-vectors based on the resonance frequencies values was illustrated on both calibration circular plates and aging aircraft panels. It was found that if the number of features is insufficient, the classification of mild damage could be deficient. However, this problem was overcome by increasing the number of features. In the simple circular plates experiments, features vectors containing as few as six resonance frequencies were found sufficient for PNN classification of damage existence and location. In aging aircraft panel, features-vectors containing 48 resonance frequencies had to be used. The PNN approach, when used in conjunction with features extraction, successfully identified both the presence of damage, and its location.

The results of this investigation revealed that the overall statistics approach, which is simplest to apply, could correctly classify near-field spectra using the dereverberated response and the correlation coefficient difference (CCD) damage metric, but it could not classify medium field spectra. The features-based PNN could correctly identify both medium-field and near-field data. The PNN approach, though more successful, is also more elaborate, since it requires two stages of data processing, first features extraction; then, classification.

6. ACKNOWLEDGMENTS

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