Monitoring Progressive Damage Development in Laminated Fiber Reinforced Composite Materials

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Monitoring Progressive Damage Development in Laminated Fiber Reinforced Composite Materials Arnab Gupta (ABSTRACT)

With increasing applications of composite materials, their health monitoring is of growing importance in engineering practice. Damage development in composite materials is more complex than for metallic materials, because in composite materials (a) multiple damage modes are simultaneously in play, and (b) individual 'damage events' that occur throughout a component's service life may neither noticeably affect its performance, nor suggest future failure. Therefore, informed health monitoring of composite components must include monitoring and analysis of their health state throughout their service life.

A crucial aspect of the health monitoring process of composites is the development of tools to help with this goal of understanding the health state of composites throughout their life. This knowledge can lead to timely anticipation of future failure in composite components, and advance the state of current technology. One, timely maintenance can be planned in advance. Two, each component's service life can be determined based on its individual health information, rather than empirical statistics of previously failed components. This dissertation develops such tools and methods.

Composite specimens of multiple ply-layups are subjected to tensile loading schemes until failure. Pencil Lead Breaks (PLBs) are used to simulate Acoustic Emission sources and generate acoustic waves that are acquired by installed piezoelectric sensors. A numerical method to estimate the arrival of wave modes from ultrasonic signals is presented. Methods are also presented that utilize PLB signals to indicate approaching failure of specimens under monotonic as well as cyclic loading. These processes have been developed prioritizing simplicity and ease-of-execution, to be adapted for practical deployment.

Monitoring Progressive Damage Development in Laminated Fiber Reinforced Composite Materials Arnab Gupta (GENERAL AUDIENCE ABSTRACT)

Composites are modern engineering materials comprising strong load-bearing elements (such as carbon fibers) embedded in a binding polymer matrix (such as epoxy). Material properties in composite materials are directional in nature, and composite plies can be combined in layers to create components with specified engineering properties. Composites are therefore increasingly being used in diverse engineering applications.

Composite materials, however, are relatively complex in their damage development and failure. Unlike in metallic materials, damage in composites can progress via several different mechanisms. Further, numerous small damage events may occur throughout the service life of a composite component, which neither noticeably affect performance, nor forewarn of impending failure. Therefore, it is of crucial importance to develop tools and methods that improve the health analysis and anticipation of future failure in composites.

This dissertation develops such methods and tools. Composite specimens with several different ply sequences are experimentally subjected to tensile loading schemes until failure. Pencil Lead Breaks (PLBs) are used to simulate Acoustic Emission stress waves throughout each experiment, and these ultrasonic waves are acquired for further data analysis using installed piezoelectric sensors. A numerical method is developed that automatically estimates the arrival times of two fundamental wave modes in sets of acquired acoustic ultrasonic signals. Methods are also developed that utilize PLB signals to anticipate future failure of composite specimens under two different loading regimes.

The contributions herein prioritize simplicity and easy execution, to be adapted for practical deployment, and are applicable for a wide variety of fiber-reinforced composites.

Dedicated to family: Some that I found by birth, and some that I discovered along the way—

You know who you are.

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Contents

	Abs	tract	ii
	Gen	eral Audience Abstract	iii
	Ack	nowledgements	v
	List	of Figures	xii
1	Intr	oduction	1
	1.1	Deterioration in Composites	1
	1.2	Synopsis of Dissertation	3
2	Lite	rature Review	5
	2.1	Lamb Waves	6
	2.2	Extensional and Flexural Wave Modes	8
	2.3	Acoustic Emission	9
	2.4	Acousto-Ultrasonics	12
	2.5	Wavelet Analysis	14
3	Det	erioration Under Monotonic Loading	22
	3.1	Abstract	22
	3.2	Introduction	23
	3.3	Procedure	26

	3.4	Result	s and Discussion	29
4	Calc	culation	n of Wave Mode Arrivals	40
	4.1	Abstra	act	40
	4.2	Introd	uction	41
		4.2.1	Acoustic Emission and Lamb Waves	41
		4.2.2	Wavelet Analysis	44
		4.2.3	Wave Mode Arrival Times	47
	4.3	Metho	od	49
		4.3.1	Experiment and Data Acquisition	49
		4.3.2	Wavelet Transform	51
	4.4	Result	S	52
		4.4.1	Arrival of Extensional Mode	52
		4.4.2	Arrival of Flexural Mode	54
		4.4.3	Peak and Prominence of Waveforms	56
		4.4.4	Programming and Performance	59
	4.5	Summ	nary	62
5	Earl	y Dete	ction of Critical Damage	64
	5.1	Abstra	act	64
	5.2	Introd	uction	65
	5.3	Backg	round	67
		5.3.1	Pencil Lead Breaks	67
		5.3.2	Wavelet Analysis and Signal Energy	68
	5.4	Metho	od	73
		5.4.1	Experiments	73
		5.4.2	Pencil Lead Breaks	76

		5.4.3 Wavelet Analysis	77
		5.4.4 Energy Peaks and Energy Ratios	79
	5.5	Results	80
	5.6	Conclusions	85
6	Con	clusions	95
6	Con 6.1	clusions Contributions of this dissertation	95 95
6	Con 6.1 6.2	clusions Contributions of this dissertation	95 95 98
6	Con 6.1 6.2	clusions Contributions of this dissertation	95 95 98

List of Figures

2.1	Schematic showing symmetric and anti-symmetric Lamb wave modes	7
2.2	Piezoelectric Sensor and its direction of sensitivity	8
2.3	Sample Acoustic Emission signal	10
2.4	Short Time Fourier Transform (STFT): basis functions and time-frequency	
	resolution	16
2.5	Wavelet Transform: basis functions and time-frequency resolution	17
2.6	Mexican Hat and Morlet Wavelets	19
2.7	Fast Fourier Transform (FFT) of a sample Pencil Lead Break (PLB) signal .	20
2.8	Scalogram plot of Continuous Wavelet Transform (CWT)	20
3.1	Schematic of experimental setup, showing position of pinducers and pencil	
	lead break locations	26
3.2	A pair of Bessel filtered pencil lead break data, showing extensional and	
	flexural modes: (a) from the first pinducer; (b) from the second pinducer.	28
3.3	Difference in arrival times, Δt , for extensional mode. Red and blue represent	
	two different data sets. Bold lines indicate mean values; lighter lines indicate	
	bounds	30

3.4	Difference in arrival times, Δt , for flexural mode. Red and blue represent	
	two different data sets. Bold lines indicate mean values; lighter lines indicate	
	bounds.	31
3.5	Wavelet Transform for Pencil Lead Breaks, performed with 0 kN load on	
	specimen, at position 1 (top) and position 4 (bottom) as shown in Fig. 3.1 .	33
3.6	Wavelet Transform for Pencil Lead Breaks, performed with 29 kN load on	
	specimen, at position 1 (top) and position 4 (bottom) as shown in Fig. 3.1 .	34
3.7	3D plot of centroidal values of frequency and total energy content over	
	time, with 0 kN, 5 kN and 10 kN load on specimen. Frequency centroids	
	and energy content are derived from wavelet transform data. Consistent	
	behavior at different loads indicates lack of deterioration. The maximum	
	value on the vertical axis is 0.025, about double the value in Fig. 3.8	35
3.8	3D plot of centroidal values of frequency and total energy content over	
	time, with 20 kN, 25 kN and 29 kN load on specimen. Frequency centroids	
	and energy content are derived from wavelet transform data. Consistent	
	behavior indicates that energy content is not affected by progressive damage	
	occurring at these loads. The maximum value on the vertical axis is 0.014,	
	about half the value in Fig. 3.7.	36
3.9	Similar to Figs. 3.7 and 3.8, this compares behavior with 0 kN and 29 kN	
	load on specimen. Energy content is about halved between negligible	
	deterioration (Fig. 3.7) and large damage (Fig. 3.8).	37
3.10	Wavelet transforms for pencil lead breaks at 0 load at: (a) position 3; and	
	(b) position 6. The features are similar to those in Fig. 3.6	38
4.1	Sample Acoustic Emission signal	43

4.2	The solid blue curve in both figures shows the real-valued Morlet wavelet.	
	In Fig. 4.2b the dashed red curve shows the sinusoidal wave that perfectly	
	matches the center of the wavelet, having a frequency of ≈ 0.7958 Hz	46
4.3	A sample ultrasonic signal with extensional and flexural modes, and its	
	wavelet decomposition components. The arrival of the extensional and	
	flexural modes are indicated by red and black dashed vertical lines	48
4.4	Piezoelectric Sensor and its direction of sensitivity	50
4.5	Schematic showing experimental sample with piezoelectric sensors attached	51
4.6	Waveform to determine the arrival of the extensional mode. Since each	
	'higher frequency' decomposition in Fig. 4.3b (bottom) indicates this arrival	
	reliably, any one of those components can be used. The actual arrival times,	
	identical to those in Fig. 4.3a, are indicated by red (extensional) and black	
	(flexural) dashed vertical lines	53
4.7	Waveform used to determine arrival of flexural mode. This is a product of	
	each of the wavelet decompositions in Fig. 4.3b (middle). The actual arrival	
	times, identical to those in Fig. 4.3a, are indicated by red (extensional) and	
	black (flexural) dashed vertical lines.	55
4.8	Relevant height measures needed to calculate the prominence parameter	
	for two peaks in a sample curve.	57
4.9	Representative signals from natural Acoustic Emission events, and algo-	
	rithmically identified arrival times of their extensional (red dashed vertical	
	line) and flexural (black dashed vertical line) modes	60
4.10	Representative signals from Pencil Lead Breaks, and algorithmically identi-	
	fied arrival times of their extensional (red dashed vertical line) and flexural	
	(black dashed vertical line) modes.	61

5.1	The solid blue curve in both figures shows the real-valued Morlet wavelet.	
	In Fig. 5.1b the dashed red curve shows the sinusoidal wave that perfectly	
	matches the center of the wavelet, having a frequency of ≈ 0.7958 Hz	71
5.2	Schematic showing experimental sample with piezoelectric sensors attached	74
5.3	Piezoelectric Sensor and its direction of sensitivity	75
5.4	Performing a Pencil Lead Break at different angles of incidence $ heta$	77
5.5	To observe the contribution of different frequency components, an FFT is	
	performed on each frequency component of the wavelet transform of a	
	representative acoustic signal. The amplitudes are normalized and plotted,	
	which clearly shows the relative peaks along the frequency axis. Lines of	
	each different color correspond to a different frequency component	78
5.6	Energy Ratios for specimen 1, with ply-layup $[0^{\circ}/90^{\circ}_{3}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	86
5.7	Energy Ratios for specimen 2, with ply-layup $[0^{\circ}/90^{\circ}_{3}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	87
5.8	Energy Ratios for specimen 3, with ply-layup $[0^{\circ}/90^{\circ}_{3}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	88
5.9	Energy Ratios for specimen 4, with ply-layup $[0^{\circ}/90^{\circ}_{3}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	89
5.10	Energy Ratios for specimen 5, with ply-layup $[0^{\circ}/\pm 60^{\circ}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	90
5.11	Energy Ratios for specimen 6, with ply-layup $[0^{\circ}/\pm 60^{\circ}]_{S}$. Blue and Red	
	curves denote data from two different sets of PLBs	91
5.12	Energy Ratios for specimen 7, with ply-layup $[90^{\circ}/\mp 30^{\circ}]_S$. Blue and Red	
	curves denote data from two different sets of PLBs	92

Chapter 1

Introduction

Every physical component evolves over time. Due to environmental conditions, service loads or unexpected loading conditions over the life of the component, its performance deteriorates until finally it can no longer provide acceptable performance. At this point, the component is said to have failed. Evidently, it is desirable that impending failure be predicted in advance for components in service, so that a replacement may be planned for. Additionally, it is also desirable, considering economic reasons and efficiency of performance, that a component not be removed prematurely from service, when considerable useful life still remains. It is for these reasons that monitoring of damage and health evolution is important.

1.1 Deterioration in Composites

Composite materials are increasingly being used in diverse engineering applications. Among these, fiber reinforced polymer composites, which can be assembled to create laminates of desired engineering properties, are most commonly used. The heterogenous nature of these composites, comprising fibers made of carbon or glass or boron or other materials embedded in a polymer matrix such as epoxy, means that deterioration of composite materials can occur through several different damage modes.

In a composite component, numerous minor deterioration events occur throughout the life of the component, through some or all possible damage modes, such as fiber breaks, matrix cracks, delaminations, and debonding between fibers and the matrix. These deterioration events occur due to the inherent variation in local material properties within the component, such as the distribution of strength and stiffness of the fibers, the localized bonding between fibers and matrix, and localized bonding between different plies in the laminate. These events are not severe enough to affect their immediate vicinities, and since such localized variations are distributed throughout the component, no single event has a significant effect on the component's life or performance. For a major portion of the service life of the component, nor do they indicate upcoming component failure. After a point, however, accumulated deterioration events do begin to affect regions adjacent to them. After this stage, they really are damage events— they adversely affect performance and finally, cumulatively, lead to failure.

Health monitoring and failure prediction in composite components is complicated by the occurrence of numerous deterioration events, none of which can specifically be linked to impending failure of the specimen. In metallic materials, which are nominally homogenous, damage usually develops in the form of a small number of cracks in regions of high stress concentration. The health of the specimen can be correlated to the crack size, and the developing cracks can be monitored to anticipate how much longer the component can remain in service. In contrast, no specific cracks can be correlated to the life or health of composite specimens. In the absence of such knowledge, the service life of composite materials is often limited to a statistically safe service time keeping in mind safety considerations. This system, while essential in the absence of more accurate life prediction, is inefficient and wasteful for components in good health.

1.2 Synopsis of Dissertation

This dissertation aims to develop tools and methods that improve the understanding of the health of composite components, and help identify future failure of composite components under various loading conditions. We proceed using the Acoustic Emission technique, and specifically make use of simulated Acoustic Emission in the form of Pencil Lead Breaks.

We begin in Chapter 2 with an overview of the literature, summarizing the current state of technology as related to Acoustic Emission, the use of Pencil Lead Breaks and their behavior, and understanding the mechanics and wave propagation in composite laminates. We also summarize the fundamental technologies and concepts needed to analyze the data that we will acquire experimentally, and the current state of how such concepts are used by other research groups.

In Chapter 3, we investigate damage development in crossply laminates subjected to a slow, monotonically increasing load until failure. This research has been published in *Materials Evaluation* journal. Here, acoustic waves generated due to Pencil Lead Breaks performed in intervals during the experiment are acquired by piezoelectric sensors, and are analyzed in several ways. We show that the difference in arrival times of the extensional and flexural wave modes can be used as an indicator of upcoming specimen failure. We further show that the energy distribution within the acquired signals, observed by performing a wavelet transform, changes in a fundamental way during the damage development process.

In Chapter 4, we develop a numerical tool to algorithmically estimate the arrival times of the extensional and flexural modes in experimentally acquired Acoustic Emission signals. This research has been accepted for publication, pending minor revisions, in *Ul*-

trasonics journal. An effective system to analyze the health state of composite components must include fast, automated algorithms to perform essential procedures. Identifying the arrival times of these wave modes is an essential but time consuming process in most cases, and this research provides the numerical algorithm to perform this task reliably and quickly. The relevant programming code is made available for public use on an internet repository.

In Chapter 5, we describe research to accurately and reliably identify future failure in composite specimens under slow cyclic loading. This research is ready to be submitted for peer-review and publication. In most cases, the most representative real-world loading regime is a cyclic load where components might fail in fatigue. This scenario is replicated in this research, where composite specimens with multiple different ply-layups are subjected to slow speed, i.e. very low frequency, cyclic loading until failure. Pencil Lead Breaks are performed during the experiment, and the energy contribution of the acquired signals is analyzed to develop a parameter that can indicate drastic changes in specimen health.

We conclude with Chapter 6, where we summarize this dissertation, and offer future avenues of further research.

Chapter 2

Literature Review

With increasing use of complex composite materials in diverse engineering applications, their health monitoring is of paramount importance. In composite materials, deterioration may develop through several different mechanisms [Proctor et al., 1983, Garg and Ishai, 1985, Bhat et al., 1994, Yoji et al., 2010]. These mechanisms, such as fiber breaks, matrix cracks, delaminations, and debonding between fibers and the matrix material, are driven not only by the geometry of the specimens and the particular loading conditions [Reif-snider et al., 2000, Subramanian et al., 1995, Reifsnider and Jamison, 1982, Reifsnider and Talug, 1980], but also by the inherent variation in the localized properties of the composite material. Some examples of such variation are in fiber stiffness and strength, bonding between different layers of the composite material, and the bonding between the fiber and the matrix material. This is very different from damage growth in metallic materials [Plumbridge, 1972, Carpinteri, 2012, Pearson, 1975], where the size and growth of a small number of cracks, usually occurring in areas of stress-concentration that are calculated before-hand, can be monitored throughout the service life of the component.

One of the major techniques to investigate the health state of composite materials is by the use of acoustic waves traveling within composites. These acoustic waves can be acquired by sensors and analyzed to understand and make predictions regarding deterioration and future failure of composite components.

2.1 Lamb Waves

The characteristics of acoustic waves propagating in a plate were first studied by Horace Lamb [Lamb, 1917]. Such waves, propagating in a 'plate', i.e. a three-dimensional structure where one dimension is much smaller in magnitude than the other two, are called Lamb waves. Unlike in an infinite medium, where acoustic waves only propagate in a finite number (two or three) of modes [Achenbach, 1973], in a plate with finite thickness two infinite sets [Viktorov, 1970, Nayfeh AH, 1989, Guo and Cawley, 1993] of Lamb wave modes may propagate (Fig. 2.1). One of these sets comprise the family of symmetric waves, whose motion is symmetrical about the mid-plane of the plate (Fig. 2.1a). Such waves are also called longitudinal waves, as the overall particle motion is in the same direction as wave propagation. The other set of Lamb waves are the anti-symmetric waves, where the motion is asymmetrical about the mid-plane of the plate (Fig. 2.1b). Such waves are also called transverse waves, as the particle motion here is perpendicular to the direction of wave propagation. Simulated videos of the particle and wave motion of these two types of waves are available on the internet [web, c].

Although Lamb's original work only considered isotropic plates, his work has been extended for anisotropic plates, for example by Nayfeh and Chimenti [Nayfeh AH, 1989] and Solie and Auld [Solie and Auld, 1973]. Lamb waves have been employed in composite materials for a long time [Deighton et al., 1981, Alleyne and Cawley, 1992] as a method to interrogate large plate-like structures [Guo and Cawley, 1993, Tan et al., 1995, Smith, 2003], since Lamb waves have the property of permeating through the entire width of the structure. More recently, propagating Lamb waves have been used for tomographic reconstruction [Hou et al., 2004, Keulen et al., 2014] and many other damage detection and wave propagation applications in complex composite materials [Schmitt et al., 2013, Janardhan and Balasubramaniam, 2014, Keulen et al., 2014, Schubert et al., 2014, Clough and Edwards, 2015, Sause et al., 2013].



⁽**b**) Anti-symmetric mode (*A*)

Figure 2.1. Schematic showing symmetric and anti-symmetric Lamb wave modes

The velocity at which Lamb waves propagate is a function of the frequency ν (or wavelength λ) of each wave, as well as the elastic properties and density of the plate [Rhee et al., 2007, Wang and Yuan, 2007]. However, the relationships may be reduced to only depend on the ratio of the plate thickness *d* to the wavelength λ , i.e. to d/λ . The same relationship may be expressed in terms of frequency ν as $d \cdot \nu$. This means that, since wave velocity is not constant but depends on the wavelength, Lamb waves are in general dispersive in nature.

2.2 Extensional and Flexural Wave Modes

Still considering Lamb waves, of special interest is the case where the wavelength of the propagating wave is greater than the thickness of the plate. In this 'thin plate' scenario, equations derived from classical plate theory can be used to describe wave motion [Gorman, 1991]. Possible modes of wave propagation are now reduced to just two: extensional and flexural [Gorman, 1991, Prosser and Gorman, 1994, Kaphle et al., 2012, Jeong and Jang, 2000b]. Both modes are composed of in-plane and out-of-plane displacement components, due to the Poisson effect. For the extensional mode, the major displacement component is in-plane, while for the flexural mode, the out-of-plane component is larger. It is found that for both isotropic and anisotropic materials, the extensional mode is not dispersive, while the flexural mode is dispersive. It can be shown that the velocities of the lowest symmetric (extensional) and antisymmetric (flexural) modes reduce to the plate wave solutions asymptotically as the plate thickness goes to zero [Viktorov, 1970, Gorman, 1991].



Figure 2.2. Piezoelectric Sensor and its direction of sensitivity

The piezoelectric ultrasonic sensors used for signal acquisition are sensitive to vibrations perpendicular to their 'face', i.e. vibrations that are out-of-plane to the plane of the sensor (Fig. 2.2 shows a schematic of a piezoelectric ultrasonic sensor). When such

a sensor is bonded or installed on the surface of a plate, it is therefore most sensitive to plate modes that are out of plane. Because of Poisson effects, the sensor may still be able to pick up vibrations due to in-plane vibration modes, but even in this case the sensor is actually acquiring only the out-of-plane components. Flexural modes typically have stronger out-of-plane components than extensional modes, and this is reflected in acquired sensor data: the extensional modes have smaller amplitudes relative to flexural modes. Additionally, the non-dispersive extensional modes generally travel at a greater velocity than the dispersive flexural modes, and therefore arrive at a sensor before the flexural components. An example can be seen in Fig. 2.3, where a sample acoustic emission signal is shown and the arrival and magnitudes of the extensional and flexural modes can be observed readily.

2.3 Acoustic Emission

Acoustic Emission (AE) waves are acoustic stress waves generated in a component due to localized load redistributions, and are used extensively for structural health monitoring applications [Curtis, 1974, Fleischmann et al., 1975, Breckenridge et al., 1975, Pao et al., 1979]. Every deterioration event within composite materials, such as fiber breaks or matrix cracks or delaminations, is accompanied by such AE waves that travel within the component. AE waves comprise multiple wave modes. In a bulk medium, they comprise longitudinal (p-wave), shear (s-wave) and Rayleigh wave modes as well as their reflections [Ledbetter and Kriz, 1982, Nayfeh AH, 1989]. In case of laminated plates, AE wave propagation is dominated by Lamb wave modes at different frequencies [Guo and Cawley, 1993, Prosser et al., 1999, Curtis, 1974].

Wave propagation and the acoustic emission technique have traditionally been used in structural health monitoring applications in one of two ways. The first application is to



(b) Sensor farther to the source of the signal.

Figure 2.3. Sample Acoustic Emission signal. Extensional and Flexural modes are indicated.

be able to locate a damaged region present in a laminate [Ziola and Gorman, 1991, Toyama et al., 2001, Toyama et al., 2003b, Lympertos and Dermatas, 2007, Leone et al., 2012]. For this, there must be a way to compute the distance of a source from a sensor. One way to do this would be to triangulate the location based on the arrival times of a certain wave mode at multiple sensors [Jingpin et al., 2008, Eaton et al., 2012]. Another way to achieve the same result would be to note the difference in arrival times of two different wave modes at the same sensor [Baxter et al., 2007]. If the dispersion characteristics of the laminate are known, the difference in arrival times would then be used to compute the distance of the source.

The second application of acoustic emission techniques is to characterize the damage occurring in a laminate [Proctor et al., 1983, Garg and Ishai, 1985, Bhat et al., 1994, Ono and Huang, 1995, Hamdi et al., 2013]. The signal acquired from a source is studied to identify its unique properties, so that it may be used as a signature for a particular damage type. Certain pattern recognition algorithms are often used, analyzing the time-amplitude data or, more commonly, the frequency spectra obtained via FFT. In some cases, the hypothesized damage types are forensically verified [Oskouei, 2009, Chang et al., 2010].

These schemes typically work very well for isotropic materials such as aluminium. However, in case of composite laminates and other composite components, the signals acquired at one or more sensors is not dependent solely on the characteristics of the source. The stress wave generated at the source travels along a certain path within the laminate, and the characteristics and health of the particular wave-path itself affects the signal that the sensors finally receive [Aggelis et al., 2012b, Scholey et al., 2010]. Moreover, since isolated damage events do occur on a global scale throughout the service life of the laminate, locating and identifying each such damage is not useful in evaluating its health state. Instead, the cumulative effect of all such damage events on the performance and properties of the laminate, such as stiffness, residual strength, or energy attenuation of acoustic waves, is of more importance.

2.4 Acousto-Ultrasonics

The essence of using Acoustic Emission techniques is to acquire a spontaneously generated signal comprising multiple frequency components and then analyzing the signal. The only problem is that the signals cannot be produced on demand, either in particular instants of time or in particular locations in space. One way around this is to use a signal generator to introduce an excitation within the component, but then the wave traveling withing the component is limited in its frequency components by the frequency components in the signal generator. The excitation signal is never as "wide-band" in terms of frequency as spontaneous acoustic emission signals are.

A better solution would be to identify a wide-band signal that could also be generated on demand. One way to produce such signals is by using piezoelectric patches [Chen et al., 2011, Dong et al., 2011, La Saponara et al., 2011, Tang et al., 2011] directly attached to the composite laminate. Another wide-band source, which produces predominantly out-of-plane excitations, is the Pencil Lead Break (PLB). Response of PLBs (also called a Hsu-Nielsen source [Hsu and Breckenridge, 1981]) have been shown to simulate acoustic emission responses in composites, and a standard configuration to perform PLBs is present in the literature [Gary and Hamstad, 1994]. The advantage of the PLB is that it is simple to use and replicate, and does not require prior installation for proper use. A large flexural component in the signal is also advantageous, as in most configurations used in experiments the end conditions would affect the extensional modes far more than the flexural components. Pencil Lead Breaks have previously been employed in health monitoring applications, both in isotropic materials [Ernst and Dual, 2014, Gorman, 1991, Ziola and Gorman, 1991, Prosser et al., 1999], as well as in composite materials [Jeong, 2001, Jeong

and Jang, 2000b, Jingpin et al., 2008].

The properties of Pencil Lead Breaks have been studied in detail by Sause [Sause, 2011], who examined the effects of the lead length and the angle of breakage of pencil leads through experiments and computer simulations. His findings are that the lead length and the angle of breakage affect the load characteristics of the Pencil Lead Break performed — but only in terms of the magnitude of the excitation. The waveform generated and the loading and unloading characteristics of the Pencil Lead Break remain consistent even when with changing lead length and angle of breakage. Therefore, the Pencil Lead Break can be considered to be an acceptable method of simulating an acoustic source.

Aggelis et al. have published articles [Aggelis et al., 2010, Aggelis et al., 2012a] on the subject of acoustic emission and wave propagation characteristics in composite laminates. In one paper [Aggelis et al., 2012a], they study the acoustic emission and wave propagation effects during tensile loading of cross-ply laminates. Loading involves 'cycles' of tensile loading and unloading, and in each cycle the maximum load is higher than the previous one. They observe that the amount of acoustic emission activity correlates well with the increasing load level, and conclude that:

"This phenomenological correlation is particularly important as (i) it allows estimation of the load based on simple observation even if there is no physical insight about the mechanisms behind the AE activity and (ii) it establishes the direct relation of the acoustic activity to loading history and consequently cumulative damage."

It is not self-evident, however, that such a correlation would hold under all circumstances [Kaiser, 1950, Nair and Cai, 2010]. While it is expected that acoustic emission activity would increase with increasing tensile loads, the same does not follow in the case of cyclic loads when the load amplitude remains constant, or nearly constant, over time. For the same reason, while it is important to be able to connect acoustic emission and wave propagation activity to loading history and cumulative damage, such a correlation cannot be based on such simple parameters as only the amount of AE activity.

Under similar cyclic loading conditions, another paper by the same group [Aggelis et al., 2010] compares the extent of acoustic emission activity during the loading and unloading phases, and observe that the extent of acoustic emission activity during the unloading phase increases significantly with increased loads (and increased damage). However, as before, a similar effect may not occur when the loading amplitude does not increase with every loading cycle.

2.5 Wavelet Analysis

Wavelet analysis (and the wavelet transform) is a numerical analysis technique to decompose a time-series signal into time and frequency space simultaneously [Gröchenig, 2001]. This decomposition into both time and frequency space is important for signals that are not stationary.

As an aside, stationary signals are those signals whose statistical parameters remain constant over time [Proakis and Manolakis, 2007]. This means that if a signal is sampled at different time intervals, the signal 'fragments acquired would have constant statistical parameters. For stationary signals, decomposition into frequency space is sufficient, and the Fourier transform is used for this purpose.

However, for non-stationary signals, i.e. signals where the statistical parameters of the signal are not uniform over periods of time, the temporal aspect of when each frequency component occurred is important. Stress waves and acoustic emission signals are transient waves and are non-stationary, and therefore wavelet analysis and the wavelet transform are important tools in their analysis. There are numerous articles in the literature [Mallat, 1989, Vetterli and Herley, 1992, Cohen and Kovacevic, 1996] that provide background and a mathematical treament of the technique. Dr. Stephane Mallat's book [Mallat, 2008] provides a comprehensive study of the subject.

Wavelet analysis has found widespread use in the wider research community. As an example, Nakken [Nakken, 1999] used the wavelet technique to study rainfall runoff variability trends. Wink and Roerdink [Wink and Roerdink, 2004] utilized waveletbased denoising techniques in functional MRI applications. In the area of structural health monitoring, La Saponara et al. [La Saponara et al., 2011, Tang et al., 2011], for example, are a group that has recently made extensive use of wavelet analysis. Kessler et al. [Kessler et al., 2002], Kishimoto et al. [Kishimoto et al., 1995], Jeong [Jeong, 2001] and collaborator [Jeong and Jang, 2000b], Qi [Qi, 2000], Suzuki et al. [Suzuki et al., 1996], Jiao et al. [Jiao et al., 2004, Jingpin et al., 2008] and others have also used the technique in various applications. Ciampa and Meo [Ciampa and Meo, 2010] and Grabowska et al. [Grabowska et al., 2008] have used wavelet analysis techniques for damage identification and source location applications in composite materials.

Donoho et al. at Stanford University prepared a set of MATLAB routines called WaveLab [web, i] to implement various wavelet analysis techniques (in conjunction with MATLAB's built-in routines). WaveLab is a popular, widely used, freely available toolset, including in the structural health monitoring area [La Saponara et al., 2011, Tang et al., 2011]. However, MATLAB's own Wavelet toolbox [web, f] and the fundamental routines it provides are quite powerful on their own, and may be used to implement different wavelet algorithms.

The idea behind wavelet analysis can be understood by drawing an analogy with windowed Fourier transforms, also known as Short Time Fourier Transforms (STFT). In STFTs, the presence of a window function helps in a way to incorporate the time dimension. Here, the Fourier transform is computed in each time window segment of the signal, thus providing an idea of when in time each frequency spectrum was observed. The drawback here is that since the size of the window is fixed, wave modes with wavelengths larger than the window size are lost and don't appear in the Fourier transforms, i.e. STFTs don't work well for low frequencies.



Figure 2.4. Basis functions and time-frequency resolution of the Short Time Fourier Transform (STFT), from [Vetterli and Herley, 1992]. (a) Basis functions, (b) Coverage of time-frequency plane.

Where Fourier transforms only use sines and cosines as basis functions, wavelet analysis uses a more general field of function as basis functions; these functions are known as wavelets. The "mother" wavelet, when modified in shape (i.e. frequency, or "scale") and in position (i.e. time), provides the means to identify different frequency components and when in time they appear. Essentially, the modified and translated wavelet is used as a template to "match" different frequency components. While this system is also not perfect, it does provide far better resolution over time and frequency then does the STFT. Compare Fig. 2.4 and Fig. 2.5, where it is observed that while for the STFT the frequency and time resolutions remain constant, for the wavelet transform these resolutions change along both axes. The mathematical differences between wavelet spectra and Fourier spectra are found in a paper by Perrier et al. [Perrier et al., 1995].



Figure 2.5. Basis functions and time-frequency resolution of the Wavelet Transform, from [Vetterli and Herley, 1992]. (a) Basis functions, (b) Coverage of time-frequency plane.

In wavelet analysis, resolutions in time and frequency come at the cost of one another. This means that at regions of high temporal fidelity the frequency fidelity is not as great, and conversely where the frequency spectra are of high resolution, temporal information is more diffuse. The parameters chosen for a particular implementation determine the particular trade offs made, and thus it is possible to tailor the analysis according to the requirements of the particular application. There are various different "mother" wavelets that can be used, and the wavelet for a particular application is usually chosen based on how well it matches the features of the signals being analyzed. Some common wavelets are the Morlet wavelet, the Daubechies wavelet, the Haar wavelet, the Mexican Hat (or Ricker) wavelet, and many others. Figure 2.6a and Fig. 2.6b show the shapes of the Mexican Hat and Morlet wavelets.

In particular, the Gabor Wavelet Transform technique, which performs the Continuous Wavelet Transform (CWT) — as opposed to the Discrete Wavelet Transform has been shown [Tang et al., 2011, Büssow, 2007] to perform well with transient signals. Among other choices of wavelets, the Morlet wavelet in particular, used with CWT has been shown to produce excellent results [Shyu and Sun, 2002].

Mathematically, the continuous wavelet transform is given by:

$$X_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t) \overline{\psi}\left(\frac{t-b}{a}\right) dt$$
(2.1)

where

- *x*(*t*) is the input signal as a function of time
- ψ(t) is the particular mother wavelet used, and must be continous both in the time and frequency domains.
- *a* (>0) is called the "scale factor", and either dilates or compresses the mother wavelet.
 The scale factor can be converted to an equivalent set of frequency values.
- *b* is the "translational factor", and moves the mother wavelet along the time axis.
- *X_w(a, b)* is the resultant output of the wavelet transform, and provides two-dimensional data corresponding to (*a, b*) values.

For example, if the Mexican Hat wavelet, shown in Fig. 2.6a, (used extensively in processing seismic data) were to be used, $\psi(t)$ above would be given by:

$$\psi(t) = (1 - x^2) \cdot \exp\left(\frac{-x^2}{2}\right)$$
 (2.2)

The real-valued Morlet wavelet, shown in Fig. 2.6b and which is used throughout this dissertation, is given by:



 $\psi(t) = \exp\left(\frac{-x^2}{2}\right) \cdot \cos 5x \tag{2.3}$

Figure 2.6. Example of "mother wavelets" used in wavelet analysis

Wavelet analysis results, in the form of wavelet coefficients, may be used in different ways. One way is to use the data to plot 3-dimensional plots with two horizontal axes representing time and frequency, and the third vertical axis showing the magnitude of the wavelet transform at that coordinate. The same representation may be made in 2-D plots using so called "heat maps" — using color schemes (instead of height) to denote different values of the wavelet coefficients. Such "heat map" style plots for wavelet-type data are referred to as scalograms [Peng et al., 2002, He et al., 2011], and are a very efficient and



Figure 2.7. Fast Fourier Transform (FFT) of a sample Pencil Lead Break (PLB) signal $\cdot 10^{-2}$



Figure 2.8. Scalogram plot of Continuous Wavelet Transform (CWT) using Morlet Wavelet, of same signal used in Fig. 2.7. The colors indicate the percentage of total signal energy being contributed by a particular (time, frequency) region.
visually simple way of displaying wavelet data.

Wavelet data can also be used as an estimate of the energy content of the signal. This can be obtained by computing and plotting the power spectrum of the data, or by using other mean energy computations, remembering that the square magnitude of a Fourieror wavelet-type coefficient is proportional to local energy [Shyu and Sun, 2002, Büssow, 2007]. Dr. La Saponara's group [Tang et al., 2011] have also developed MATLAB code to further analyze wavelet data in terms of creating area plots from the contour plot that MATLAB CWT computations normally produce.

Figure 2.7 and Fig. 2.8 show the FFT and the wavelet transform using the Morlet wavelet for the same ultrasonic signal, in this case from a PLB. In Fig. 2.7 the frequency spectrum is observed, but there is no information about the time instants for the arrival of each frequency component. In contrast, in Fig. 2.8, the vertical axis shows the frequency components while the horizontal axis shows when in time each frequency component arrived. For analysis for transient signals such as acoustic emission or PLB signals, such time-frequency information obtained from wavelet analysis is extremely useful.

Chapter 3

Deterioration Under Monotonic Loading

Publication Information

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3.1 Abstract

Acoustic emission testing (AE) is an important tool in structural health monitoring of composite materials. Characterization of service-induced damage in a component in service would be a major step in this technology. In this direction, the present study examines simulated AE signals from cross-ply composite laminates. Tensile tests were performed on test specimens, and pencil lead breaks (PLB) were done at various loads

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until failure. AE data were acquired using pinducer ultrasonic sensors, and the data were analyzed in order to identify damage development in the specimens using variation in the PLB data. It was seen that different analysis techniques can be used to monitor damage development.

Keywords: acoustic emission, acousto-ultrasonics, damage mechanics, Lamb waves, composite materials

3.2 Introduction

The performance of every component evolves over time, as localized variations in stresses occur or as external loads arise that the material is not able to sustain. In either case, the material reacts by undergoing certain internal rearrangements, and as a result the material is said to deteriorate. In metals, this may occur through the formation of microcracks in the material or the propagation of existing cracks; in fiber reinforced polymer materials, this occurs through a number of mechanisms, such as delamination, matrix cracks, fiber matrix debonding or fiber breaks [Stinchcomb, 1986]. Whatever the particular mechanism may be (in metals and composites alike), this deterioration is accompanied by the generation and propagation of stress waves — ultrasonic acoustic waves known as acoustic emission. Accumulated deterioration, or deterioration in the same local region, can damage the material to an extent that it finally undergoes failure.

Acoustic emission testing (AE) is characterized by having multiple wave modes traveling at different frequencies and velocities [Fleischmann et al., 1975, Glennie and Summerscales, 1986, Scruby, 1987]. The propagation, modes and frequencies are dictated by material properties, loading conditions and boundary conditions. The detection and analysis of AE forms a major method of nondestructive testing.

Damage development and ultimate failure of metallic materials usually originates

wherever a microcrack forms and propagates. In the case of polymer composites, damage development is a little more complex. Because of the inherent nature of composite materials (numerous fibers embedded in a polymer matrix), a single deterioration event does not control the performance of the material [Stinchcomb, 1986]. Small, singular events can occur at various locations in the material over a prolonged service period without having any effects in the performance of the material. Damage in composites begins to occur when these events cease to be random and globally located, and begin to be concentrated in particular regions; this phase is the damage development localization. Only beyond this stage does the performance of the material begin to significantly diminish, and failure of the component becomes probable.

It is important, for this reason, to follow damage development in a component made of composites and how the component's performance and properties deteriorate over its life. It is also important to locate damage sources and identify the stage where damage development localization begins. As long as the material properties, such as stiffness, do not diminish, and as long as deterioration events are not concentrated in certain regions, the material can remain in service.

AE is an important method in damage study and life prediction of composite materials. AE can be monitored to study damage evolution (since AE characteristics are dependent upon material properties), as well as to identify source locations (since different wave modes travel at different velocities).

Previous and current research on AE monitoring focuses mostly on source location and the characterization of AE signals to identify particular damage mechanisms [Gho, 2002, Gle, 1985, Rao et al., 2007, Ono and Huang, 1995, Surgeon and Wevers, 1999]. Some work has been done on the cumulative effects of damage, but they are either to validate a particular theory, or they use more indirect methods [Doctor et al., 1996, Subramanian et al., 1995, Toyama et al., 2002]. Even with in-depth research on damage evolution, there is ample need for more work [Bussiba et al., 2008].

Lamb wave techniques are used extensively to detect damage, and various techniques involving the energy content of the waves as well as their arrival times and wave speeds are considered [Kessler et al., 2002, Lee and Staszewski, 2003a, Lee and Staszewski, 2003b, Lee et al., 2011, Valdes and Soutis, 2002]. However, most of such research focuses on the detection of damage, rather than on identifying characteristics that can identify transitions in precursor damage development.

The first step towards observing damage development is to be able to monitor how stress wave propagation changes over the service life of a composite material. For this purpose, a simulated AE source is needed that will be reproducible over multiple repetitions. A pencil lead break (Hsu-Nielsen source; PLB) provides such a source [Gary and Hamstad, 1994]. If a PLB can be done on a sample as it deteriorates and ultimately fails, the changes, if any, in the PLB AE signals due to damage evolution in the material can be observed. The source remains the same; therefore, any changes in the AE signals acquired can be attributed to damage in the component.

In the present study, quasi-static tensile loading until failure of composite coupons (dimensions 25mm × 300mm) was done, and PLBs were performed on the coupons at the beginning and at various points during the loading process. PLBs were performed using conventional 0.3mm 2H pencil leads in a mechanical pencil [Gary and Hamstad, 1994, Gorman, 1991, Hamstad, 1982]. AE signals from the PLB, as well as from damage to the material, were recorded. The signals from the PLB were in particular analyzed for changes over the course of the experiments.

3.3 Procedure

An eight-ply $[0^{\circ}/90^{\circ}_{3}]_{S}$ laminate was produced in-house, using a 5245C pre-impregnated system (with G40-600 unidirectional carbon fibers), and then machined to create 25 mm × 300 mm coupons.

For each experiment, a coupon was loaded onto a standard tensile testing machine fitted with a 50 kN load cell, and was loaded under displacement control at a rate of 1 mm/min.

Data acquisition was done using two standard pinducers, each of which had a sensing region of less than 2 mm in diameter. The pinducers were each mounted in a fixture that was built in-house, which in turn was attached to the coupon using rubber bands (see Fig. 3.1). The attachment is such that the only contact points on the coupon are the pinducer itself and two other support points on the fixture.



Figure 3.1. Schematic of experimental setup, showing position of pinducers and pencil lead break locations.

PLBs were done at 5 kN load intervals, starting at zero load. The last set of PLBs was done at 29 kN instead of at 30 kN, as some of the coupons failed around the 30 kN mark. The PLBs were done at predetermined locations (Fig. 3.1), both between the two sensors, as well as at the two extremities of the coupon gage section. The crosshead displacement of the tensile testing machine was stopped while the PLBs were being performed. The PLB locations were chosen so that in some cases (positions 1 to 3) the AE signal traveled along

the 0° direction, while in others (positions 4 to 6) the AE signals traveled at an angle to the 0° direction before reaching the sensors.

An automated data acquisition system with two input channels was used. An automated acquisition mode was set up where the software awaits a trigger signal and then records data for a certain number of data points. The program was also capable of retaining whatever signal was received before the trigger signal arrived (for a certain number of data points, which can be specified), so these data could also be recorded when a trigger signal arrives. This feature was enabled to ensure that a complete record of detected signals from both sensors was always obtained. This is important when the source is farther from the trigger sensor than the other sensor; in such a case, the signal passes through the other sensor before the acquisition system is triggered. Data was acquired in 12-bit mode at 25 MHz with a range of $\pm 2V$, with 7168 data points post-trigger and 3072 data points pretrigger, for a total of 10 240 data points, corresponding to 409.6 μ s for each AE signal detected.

For ease of analysis and observation, the data obtained were digitally filtered. Since it has a flat frequency response, a Bessel filter was used in bandpass mode, from 50 kHz to 1 MHz, with four poles. This band was chosen based on previous work, considering the effects of mode superposition and allowing a wide enough frequency band for meaningful analyses, while at the same time removing extraneous noise [Prosser et al., 1999].

The filtered signal is used to find the arrival times of acquired signals at the pinducers. This is done by plotting the signals over time and visually ascertaining their arrival times; this is the most reliable technique. For each acquired signal, arrival times for two wave modes are identified: an extensional mode and a flexural mode. As an example, Fig. 3.2 shows the data record from a PLB done at location 2, after Bessel filtering. The two plots correspond to the signals detected by the two piezoelectric sensors. As labeled in the figures, the arrivals of the extensional and flexural modes are clearly identifiable.



Figure 3.2. A pair of Bessel filtered pencil lead break data, showing extensional and flexural modes: (a) from the first pinducer; (b) from the second pinducer.

Filtered signals were also used to perform wavelet transforms, which is a numerical technique used to discriminate data both in terms of frequency and time [Kishimoto et al., 1995]. This is in contrast to the usual fast Fourier transform, which only transforms the data to a frequency domain. Data from the wavelet transform shows the amplitude of the signal at each time instant in the data record over a frequency distribution. This is a very handy tool, as both the arrival times of different signal components, as well as their frequency distributions, can be observed from one plot. The wavelet transform is a common tool used in AE monitoring applications [Jeong, 2001, Jiao et al., 2004, Qi, 2000].

It is assumed that the relative positions of the pinducers on the coupon under load

remain constant as load increases. In reality, as the coupon extends under load, the relative distance between the sensors increases slightly. Based on the present testing technique, this translates to an increase in the distance over which AE calculations are done, and for the same wave speed, should translate to an increase in the parameter Δt , as described in the next section. Since it will become evident that the results indicate precisely the opposite effect (a decrease in Δt) to be significant, it can be said that this assumption is a safe one for the present study.

3.4 **Results and Discussion**

The coupons underwent deterioration as tensile load increased. The first spontaneous AE from deterioration were recorded at approximately 8 kN load, and the rate of AE increased with time, as damage developed. By 25 kN, there was visible damage to the specimens (fibers broken along the surface), and there were loud, audible sounds from further deterioration. The specimens finally broke spectacularly at approximately 31 kN. From only visual and aural observation, there was serious damage to the specimen at 25 kN, and at this point failure was evidently a definite possibility.

As described earlier, arrival times of the extensional and flexural modes were found for each pair of sensor data corresponding to a PLB. Further, the difference in the arrival times (Δt) of the signals at the two sensors was also computed. The Δt was calculated for PLB positions 2 and 3, because in these two cases the signal travels along the same straight line as it arrives first at one sensor and then the next. In the other cases, the signal travels along different paths as it travels to the two sensors.

In Fig. 3.3 and Fig. 3.4, the difference in arrival times (Δt) is plotted over increasing tensile load. Red and blue series correspond to two separate data sets. Bold lines represent mean Δt values obtained from multiple PLBs done at each load level; lighter lines show



the upper and lower bounds from those multiple measurements.

Figure 3.3. Difference in arrival times, Δt , for extensional mode. Red and blue represent two different data sets. Bold lines indicate mean values; lighter lines indicate bounds.

Pinducers used in the experiments are essentially sensitive to out-of-plane vibrations. The experiment was set up such that PLBs were initiated on the same surface to which the pinducers are attached. This means that the flexural modes generated by the PLBs are more energetic and have a larger amplitude than extensional modes generated. The signal-to-noise ratio for the flexural modes is much better than that for extensional modes, and this explains the slightly larger experimental variation in extensional mode data than in flexural mode data.

For both extensional and flexural modes, it was observed that the Δt values remained uniform up to 10 kN. This is despite spontaneous AE being detected from ap-



Figure 3.4. Difference in arrival times, Δt , for flexural mode. Red and blue represent two different data sets. Bold lines indicate mean values; lighter lines indicate bounds.

proximately 8 kN. This means that up to approximately 10 kN, there was no effect of note on wave speeds and, hence, stiffness. The Δt values increased at 15 kN, indicating that there was enough deterioration in the coupon to affect wave speeds. However, the rate of increase of Δt dropped after this point (at 20 and 25 kN), and just before failure (29 kN) the slope was negative (that is, the Δt decreased). In one case, a decrease in Δt was not observed before failure, but even in this case, the Δt remained quite uniform between 20 and 29 kN. The behavior is counterintuitive in that it is expected that with increasing damage, the Δt should continue to increase significantly with increasing damage and approaching failure.

The variations observed in Δt indicate that the transition from global deterioration

to localized damage development begins at approximately 15 kN. However, the subsequent counterintuitive behavior indicates that the mechanism through which damage develops in a localized region is not well understood, and that techniques based solely on wave speed or material stiffness measurement may not be sufficient to accurately predict impending failure.

Plots obtained from wavelet transform data show the amplitude (energy) of an AE signal as a function of frequency and time, where red is the highest amplitude, and purple is the lowest. It is observed that plots at 0, 10 and 15 kN (not shown due to space constraints) display very similar features in terms of distribution of energy over time and at different frequencies. Differences start appearing 15 kN onwards, where it is observed that the energy distribution starts changing. Where at lower loads most of the energy was concentrated towards the beginning of the data record, now the energy is much more distributed over time (that is, over a much longer portion of the data record). Also, it can be inferred visually that much of the energy appears at a lower frequency as load (and damage) on the specimen increases.

The variation can be best summarized by comparing Figs. 3.5 and 3.6, which compares wavelet transform plots at 0 and 29 kN respectively. Moreover, in each figure, the plot at the top is for the case where the pinducer receives signals traveling along the 0° direction (PLB at position 1); the bottom plot is when the signal travels at an angle to the fiber direction in the top ply (PLB at position 4). Comparing Figs. 3.5 and 3.6, it is evident that at 29 kN the energy is much more distributed over time than at 0 kN, and that the distribution has also shifted, overall, towards lower frequencies. The plots from position 4 indicate that attenuation of AE signals is much higher when the signal travels at an angle to the fiber direction.

Wavelet transform plots, as shown in Fig. 3.5 and Fig. 3.6, are not amenable to easy comparison over different loads. Therefore, the wavelet transform data were further used



Figure 3.5. Wavelet Transform for Pencil Lead Breaks, performed with 0 kN load on specimen, at position 1 (top) and position 4 (bottom) as shown in Fig. 3.1

to calculate centroidal values of frequency, as well as total energy, for each time step in the wavelet transform. This centroidal frequency can be described as a representative value of frequency for that time step. The total energy content of signals as they propagate through a certain region is also indicative of the health of material in that region; more damage leads to more energy dissipation, as seen in the comparison between Fig. 3.5 and Fig. 3.6. Thus, meaningful observations can be made by plotting the total energy and the centroidal frequency over time and by noting how the plots change with increasing load. Figures 3.7 to 3.9 are 3D plots with these parameters (time, frequency centroid and total energy) as the three axes. The figures correspond to PLBs done at position 2 and acquired



Figure 3.6. Wavelet Transform for Pencil Lead Breaks, performed with 29 kN load on specimen, at position 1 (top) and position 4 (bottom) as shown in Fig. 3.1

at the sensor farther from the PLB location. They are representative of the case where the signals travel along the 0° direction.

Figure 3.7 shows plots for 0 to 10 kN, where it is observed that the plots are quite uniform, indicating as before that material health has not started to deteriorate. It is expected that with increasing deterioration, energy content in the signals will diminish, and this is observed in Fig. 3.9, which compares the plots at 0 and 29 kN. However, this diminishing effect is not continuous throughout the loading process; the energy content and frequency characteristics remain very similar from 20 kN up to just before failure at 29 kN (Fig. 3.8). In Fig. 3.8, the variation in amplitudes is not in order of increasing load;



Figure 3.7. 3D plot of centroidal values of frequency and total energy content over time, with 0 kN, 5 kN and 10 kN load on specimen. Frequency centroids and energy content are derived from wavelet transform data. Consistent behavior at different loads indicates lack of deterioration. The maximum value on the vertical axis is 0.025, about double the value in Fig. 3.8.

the highest amplitude corresponds to 25 kN, with those for 20 and 29 kN on either side of it. Of course, all three values are very close to each other, approximately half the value at 0 kN load (Fig. 3.9).

This is a similar trend to what was observed with the difference in arrival times, Δt , and indicates that it may be insufficient to use only wave-speed and frequency characteristics to accurately predict the onset of failure. Deterioration and damage can be observed, but not damage development to the extent of being able to predict when failure will occur.

It must be remembered, however, that damage in the coupon can only be identified based on variation, rather than through absolute numbers or properties. It is necessary to



Figure 3.8. 3D plot of centroidal values of frequency and total energy content over time, with 20 kN, 25 kN and 29 kN load on specimen. Frequency centroids and energy content are derived from wavelet transform data. Consistent behavior indicates that energy content is not affected by progressive damage occurring at these loads. The maximum value on the vertical axis is 0.014, about half the value in Fig. 3.7.

be aware of the properties being monitored with the coupon in its initial state (little or no damage) to be able to infer later that damage has occurred. This is especially true of the wavelet transforms. The relatively lower frequency, lower energy plots associated with a damaged coupon can easily be accounted for in other circumstances to distance from the sensor, or to a cross-fiber direction of the source. Both of those situations also attenuate AE signals and shift their frequencies downwards. As an example, consider the wavelet transform plots in Fig. 3.6 and Fig. 3.10. Fig. 3.6 shows data from PLBs done closer to the sensor just before failure; Fig. 3.10 shows data from PLBs done further away from the sensor, but at zero load. The characteristics seen in the two figures are similar, and it is not



Figure 3.9. Similar to Figs. 3.7 and 3.8, this compares behavior with 0 kN and 29 kN load on specimen. Energy content is about halved between negligible deterioration (Fig. 3.7) and large damage (Fig. 3.8).

a simple matter to distinguish, without adequate extra information, between the two sets and identify the one that indicates significant damage. Thus, it is important to monitor and compare AE signals over time, as well as between neighboring sensors, to be able to identify damage and remaining life.

It is also important to note that the observed parameters only indicate the damage state of the region through which the particular AE waves propagate. This explains the variations between individual PLB signals; some pathways, even adjacent to each other, carried the waves better than others. Thus, it may be necessary to have multiple sensors in different directions and locations, to be able to consistently monitor damage.



Figure 3.10. Wavelet transforms for pencil lead breaks at 0 load at: (a) position 3; and (b) position 6. The features are similar to those in Fig. 3.6.

Conclusion

It is seen that simulated AE signals generated from PLBs do show varying AE parameters over time. This shows that it is possible, by monitoring a component over time, to study damage development. This process does not necessarily require the knowledge and identification of each individual damage event; instead, a holistic view of the properties and performance of the component can be adopted. It was seen that multiple parameters, such as differences in arrival times and wavelet transforms, could be used for monitoring. It is expected that this methodology can be ultimately extended and implemented using real AE generated from samples during damage evolution. In this regard, further research and analysis are ongoing to study the load-induced AE acquired during these experiments. In case of the PLB simulated AE signals, the difference in arrival times between the two sensors stayed consistent as long as there was little damage in the coupon, even after AE had started due to deterioration. The difference increased appreciably when there was more damage. However, this technique did not indicate subsequent incremental damage as load on the coupon increased.

In the case of wavelet transforms, there was variation in the frequency and energy distributions with increasing damage, but it is important to note that such frequency and energy distributions can also occur when the AE source is far from the sensor, and when the source is in a cross-fiber direction. Thus, monitoring must be done over time and between multiple sensors to find variations that indicate damage.

The only indication of approaching failure was a decrease in Δt in Fig. 3.3 and Fig. 3.4, and this phenomenon needs further analysis to ascertain its source and mechanisms. It was also observed that present techniques, while indicating the presence of damage, are not well equipped to show incremental damage with increasing load and indicate imminent failure of the material. New or modified techniques must be developed to address these requirements.

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Chapter 4

Calculation of Wave Mode Arrivals

Publication Information

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A. Gupta^{*} and J.C. Duke, Jr.[†] "Identifying the arrival of extensional and flexural wave modes using wavelet decomposition of ultrasonic signals".

4.1 Abstract

In health monitoring applications of composite materials, the health state of specimens is often evaluated using naturally occurring and simulated Acoustic Emission stress waves. For such applications, identifying the arrival times of the extensional and flexural wave modes from acquired signals is a crucial step, and must be performed reliably and potentially on large sets of signals. This article proposes using the wavelet decomposition

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of a signal to develop a fast, algorithmic and automated approach to estimate the arrival times of the extensional and flexural wave modes. Algorithms are developed that estimate the two arrival times using wavelet decomposition data, and which can be employed to consistently and reliably identify the arrival times from large sets of signals iteratively. MATLAB scripts to automatically execute the algorithms are also developed, and are made available online.

Keywords: Arrival Time; Acoustic Emission; Composite Materials; Wavelet Analysis; Data Analysis

4.2 Introduction

4.2.1 Acoustic Emission and Lamb Waves

One of the major methods of studying the health state of composite materials is to use Acoustic Emission (AE) signals [Scruby, 1987, Fleischmann et al., 1975, Prosser and Gorman, 1994]. The acoustic stress waves that are generated any time a localized load redistribution or energy release event occurs in a material are referred to as Acoustic Emission. In metallic materials, AE is generated any time a crack is created or propagated; in composite specimens, AE is generated due to a variety of events, such as fiber breaks, matrix cracks and delaminations [Proctor et al., 1983, Garg and Ishai, 1985, Bhat et al., 1994]. In contrast with such natural AE, acoustic stress waves can also be generated by the sudden removal of a small concentrated load on the specimen. Such a sudden load removal can be used to generate simulated AE (since this simulates load-redistributions that generate natural AE).

In specimens taking the shape of 'plates', i.e. where one dimension is much smaller than the other two dimensions, Lamb wave modes dominate [Prosser et al., 1999, Guo and Cawley, 1993, Lamb, 1917] AE wave propagation. Specifically, two infinite sets of Lamb wave modes propagate: (a) symmetric modes, or longitudinal modes, with vibrations symmetrical about the midplane of the plate, and (b) anti-symmetric modes, or transverse modes, with vibrations anti-symmetric about the midplane. When the propagating waves have wavelengths greater than the thickness of the plate, the plate can be termed a 'thin plate'. In such plates, only two Lamb wave modes propagate: the Extensional and Flexural mode [Gorman, 1991, Prosser and Gorman, 1994]. The extensional mode is dominated by in-plane displacements and are not dispersive in nature. The flexural mode is dispersive, i.e. their wave velocities vary according to frequency, and is dominated by out-of-plane displacements [Jeong and Jang, 2000b].

In acoustic emission testing, these extensional and flexural modes are of most interest, since many specimens under consideration satisfy the 'thin plate' criterion. Further, since in most cases the sensors that acquire the signals are attached to the 'face' of the plate, these sensors only detect the out-of-plane components of any propagating waves. For the extensional mode, the out-of-plane component is much smaller than its in-plane component; for the flexural mode this is exactly reversed. Therefore, for most cases, the acquired signals have a small extensional mode component arriving first, followed by a larger flexural mode component.

A sample AE signal, as acquired by two sensors along the same path traveled by the stress wave, is shown in Fig. 4.1. The flexural mode in Fig. 4.1a arrives soon after the extensional mode, indicating that the source is quite near to the sensor. On the other hand, in Fig. 4.1b the time separation between the arrival of the two wave modes is larger, showing that the sensor is farther from the signal source. Considering the same AE wave being detected by two sensors, this difference in arrival between the extensional and flexural modes, as well as the difference between the signal amplitudes, provide clues as to the location of the signal source.



(b) Sensor farther to the source of the signal.

Figure 4.1. Sample Acoustic Emission signal. Extensional and Flexural modes are indicated.

4.2.2 Wavelet Analysis

Wavelet analysis [Mallat, 2008] is an important tool [Mallat, 1989, Vetterli and Herley, 1992] in the time-frequency analysis of transient signals such as ultrasonic stress waves. The Fourier transform shows the frequency content of the entire signal, but the temporal aspects of the frequency components are lost. The windowed Fourier Transform attempts to improve on this, but has the disadvantage of using a time window of constant time width, thereby losing any information about wave components whose wavelengths are longer than the window width. The wavelet transform provides a versatile method to discriminate signal components along both the time and frequency axes.

Similar to the Fourier transform, the basic idea of the wavelet transform is to use a basis function (called the 'mother wavelet') to compare and characterize different portions of the signal. Unlike the Fourier transform, which only uses sine and cosine waves as basis functions and their higher harmonics to match higher frequency components, the wavelet transform may use many different kinds of mother wavelets. The mother wavelet has the property of being transient, i.e. having non-zero amplitude only for a small duration in time. In addition, the wavelet transform performs two operations [Vetterli and Herley, 1992] to identify different frequency components appearing in different time positions in the signal: (a) translation of the mother wavelet along the time axis, and (b) dilatation and contraction of the mother wavelet to match different frequencies. The mathematical differences between Wavelet spectra and Fourier spectra are described by Perrier et al. [Perrier et al., 1995].

The Gabor Wavelet Transform, or the Continuous Wavelet Transform (CWT), performs well [Tang et al., 2011] with transient signals, and is given by:

$$X_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t) \overline{\psi}\left(\frac{t-b}{a}\right) dt$$
(4.1)

where

- x(t) is the input signal as a function of time
- ψ(t) is the particular mother wavelet used, and must be continous both in the time and frequency domains. ψ(t) denotes the complex conjugate of ψ(t).
- *a* (>0) is called the "scale factor", and either dilates or compresses the mother wavelet.
 The scale factor can be converted to an equivalent set of frequency values.
- *b* is the "translational factor", and moves the mother wavelet along the time axis.
- *X_w(a, b)* is the resultant output of the wavelet transform, and provides two-dimensional data corresponding to (*a, b*) values.

Among many choices for mother wavelets that satisfy the necessary conditions, the Morlet Wavelet in particular has been shown [Shyu and Sun, 2002] to produce excellent results with transient signals. This article utilizes the real-valued Morlet Wavelet, shown in Fig. 4.2a, which is given by

$$\psi(t) = \exp\left(\frac{-t^2}{2}\right) \cdot \cos 5t \tag{4.2}$$

The relationship between the wavelet scale factors and the corresponding frequency values is given by:

$$f_a = \frac{f_c}{a \cdot t} = \frac{f_c \cdot f_s}{a} \tag{4.3}$$

where

• f_c is the center frequency of the particular wavelet in use. Referring to Eq. (4.2), the Morlet wavelet reduces to $\cos 5t$ when t = 0; therefore, the center frequency of the

wavelet is given by $\frac{5}{2\pi}$ Hz. This is confirmed in Fig. 4.2b, where a sinusoidal wave with a frequency of $\frac{5}{2\pi}$ i.e. ≈ 0.7958 Hz perfectly matches the center of the wavelet.

- *a* is the scale value being converted.
- *t* is the time period of sampling, i.e. the time duration between acquisition of consecutive data samples.
- f_s is the sampling frequency, i.e. number of times per second data is acquired. Evidently, $f_s = 1/t$.
- f_a is the frequency value corresponding to the scale value a.



Figure 4.2. The solid blue curve in both figures shows the real-valued Morlet wavelet. In Fig. 4.2b the dashed red curve shows the sinusoidal wave that perfectly matches the center of the wavelet, having a frequency of ≈ 0.7958 Hz.

The output obtained from the wavelet transform of a digital signal is in the form of sets of coefficients, with (a) the number of sets equalling the number of scales specified, and (b) each set containing the same number of elements as the original signal. (In terms of matrices, a wavelet transform with *s* scales, performed on a signal with *n* data points, produces as output a matrix of dimensions $s \times n$.) The 'frequency matching' with the scale

values is not perfectly discrete, and each wavelet component contains signal components 'around' the matched frequency. Each set of coefficients (i.e. each row of the matrix, sized $1 \times n$) can therefore be thought to represent the portion of the signal that is centered around the frequency corresponding to the specified scale value. The output of the wavelet transform can therefore also be called the wavelet decomposition, since it decomposes the original signal into components corresponding to frequencies represented by specified scale values. For example, Fig. 4.3, discussed in more detail in Section 4.3.2, shows an AE signal and its wavelet decompositions obtained through a Morlet wavelet transform.

4.2.3 Wave Mode Arrival Times

In analyzing Acoustic Emission signals, identifying the arrival times of the extensional and flexural modes is a crucial step. The common use is in locating the source of AE events, where a 'triangulation' of sorts is employed, using one or more wave modes acquired via one or more sensors [Ernst and Dual, 2014, Lympertos and Dermatas, 2007, Toyama et al., 2003b, Leone et al., 2012, Jeong and Jang, 2000a].

Only a few advanced methods to identify arrival times using the wavelet transform are found in the literature. For example, Avanesians and Momayez [Avanesians and Momayez, 2015] employ the synchro-squeeze technique and further algorithms, and need to analyze each signal individually. This technique is useful for the particular situation where the wave modes overlap completely, however in the vast majority of cases the sensor is far enough from the source that the extensional and flexural modes have at least some separation. Pomponi et al. [Pomponi et al., 2015] also utilize the wavelet transform, but they focus their effort towards extremely noisy signals. Their process utilizes a denoising algorithm in the form of 'block thresholding' and 'neighboring concepts', and then attempts to model each signal to find the 'Probability of Presence (PoP)' [Pomponi



(b) Wavelet decomposition of the same signal (i) top: below sensor sensitivity range; (ii) middle: at 'lower' frequencies; and (iii) bottom: at 'higher' frequencies. All three figures share the same units along the horizontal axis.

Figure 4.3. A sample ultrasonic signal with extensional and flexural modes, and its wavelet decomposition components. The arrival of the extensional and flexural modes are indicated by red and black dashed vertical lines.

et al., 2015] at each time instant.

This article proposes the use of the wavelet transform to design a novel, algorithmic, and relatively simple method to identify the extensional and flexural modes. The method only needs the specification of initial parameters, and can be implemented via scripting methods on large sets of acquired data.

4.3 Method

4.3.1 Experiment and Data Acquisition

The ultrasonic signals used for this article are acquired through mechanical testing experiments on composite test coupons. Using a composite pre-impregnated material (5245C) with unidirectional carbon fibers (G40-600), the coupons are prepared in-house in the form of thin plates about 2 mm thick, nominally measuring $12 \text{ in} \times 12 \text{ in} (\approx 300 \text{ mm} \times 300 \text{ mm})$. The panels are then machined into test coupons measuring $12 \text{ in} \times 1 \text{ in} (\approx 300 \text{ mm} \times 25 \text{ mm})$. The test coupons are created to have multiple different ply layups — $[0^\circ/90^\circ_3]_S$, $[90^\circ/0^\circ_3]_S$, $[0^\circ/\pm 60^\circ]_S$ and $[90^\circ/\mp 30^\circ]_S$ — and are tested under very low-frequency tensile-tensile cyclic loading until they undergo fatigue failure. The loading limits of the cyclic loading are different for coupons with different ply layups, and may additionally be slightly different between coupons of the same ply layup. This is to account for varying strengths along the direction of loading between different ply-layups and between specimens even with the same layup, and to restrict the fatigue life of the specimens to a reasonably low value (< 15000 cycles to failure).

Data acquisition is done using two piezoelectric ultrasonic sensors, specifically model SE1000-H manufactured by Score-Atlanta [web, a] (a representative schematic is shown in Fig. 4.4), that have a stable frequency response from ≈ 50 kHz to ≈ 500 kHz.



Figure 4.4. Piezoelectric Sensor and its direction of sensitivity

The sensors have an active region of a circle of diameter $\approx 2 \text{ mm}$ and are sensitive to vibrations perpendicular to its 'face', as shown in Fig. 4.4. The sensors are held to the test specimen using rubber bands and a simple wood support, and a silicone based grease-like lubricant [web, d, web, b] is used in the interface between the sensor's face and the specimen to achieve consistent mechanical wave transfer from the specimen to the sensor. This mounting method is secure enough to (a) ensure consistent contact between specimen and sensor and (b) prevent sliding of the sensors along the specimen surface. A schematic of the experimental setup is shown in Fig. 4.5, where the large blue circles represent the piezoelectric sensors.

The data acquisition software is set to capture data every time the vibrations it receives (out-of-plane to the specimen surface) rises above a minimal threshold. The software is equipped with a circular buffer whereby once data capture is triggered, it can capture data both after as well as before the trigger. This mechanism is utilized to effectively capture data from both sensors, one of which is set as the 'trigger' sensor. When the source of the signal is far from the trigger sensor but close to the second sensor, the signal arrives at the trigger sensor after it has already reached the second sensor. In this case, the entirety of the signal at the second sensor can only be acquired if the data acquisition system can capture data at time points before data capture is triggered.



Figure 4.5. Schematic showing experimental sample with piezoelectric sensors attached. Locations marked (a), (b) and (c) indicate locations where Pencil Lead Breaks are performed. Blue circles represent locations where piezoelectric sensors are attached.

In addition to acquiring signals from natural Acoustic Emission events that occur during the life of the specimen, signals from simulated Acoustic Emission events are also acquired. These simulated events are created by performing Pencil Lead Breaks (PLBs), also known as Hsu-Nielsen source, which have been long used [Gary and Hamstad, 1994, Sause, 2011] as a standard way to create wide-band simulated Acoustic Emission signals. PLBs are performed using a mechanical pencil with 0.3 mm 2H lead, and involve extending a standard length of pencil lead from the pencil (\approx 4mm) and pressing the lead on the surface of the specimen until it breaks. This process exerts a point load on the specimen which is then suddenly removed; this closely resembles natural Acoustic Emission events where accumulated stress is suddenly removed due to a damage event. PLBs are performed at pre-determined locations, shown as positions (a), (b) and (c) in Fig. 4.5.

4.3.2 Wavelet Transform

The real-valued Morlet wavelet is used to perform the wavelet transform. In doing so, the scale values should be chosen such that the entire frequency spectrum of sensitivity is covered. Therefore, the frequencies chosen (in kHz) are: 15, 40, 70, 120, 170, 220, 270, 310, 360, 420, 480, 530. These values are converted using Eq. (4.3) to the appropriate scale values. Figure 4.3 shows a sample ultrasonic signal (Fig. 4.3a), as well as its wavelet

decomposition in separate groups of frequency regions (Fig. 4.3b). The actual arrival times of the extensional and flexural modes for the sample signal are also shown (in Figs. 4.3, 4.6 and 4.7) as red and black dashed vertical lines at the appropriate time positions.

It can be seen that the first two wavelet components, centered around 15 kHz and 40 kHz, only appear to be simple sinusoidal waves devoid of much information content that correlates to the actual signal (Fig. 4.3b, top). The next group of wavelet components (Fig. 4.3b, middle) centered around 70 kHz, 120 kHz, 170 kHz, 220 kHz and 270 kHz can be classified as the 'lower' frequencies, where it is expected that the flexural mode will be prominent. Here, it is evident that the small extensional mode component does not arrive exactly at the red dashed line. On the other hand, the flexural mode components clearly overlap with the black dashed line, although a clear and unambiguous arrival time for these modes cannot be identified yet. Finally, the 'higher' frequency components centered around 310 kHz, 360 kHz, 420 kHz, 480 kHz and 530 kHz are shown in Fig. 4.3b, bottom. Here, it is evident that here the arrival of the extensional mode coincides perfectly with the actual arrival of the extensional mode (red dashed line).

4.4 Results

4.4.1 Arrival of Extensional Mode

The extensional mode always travels faster than the flexural mode, and is expected to arrive at the sensor before the flexural mode arrives. Further, the extensional mode always comprises higher frequency components. As already discussed above, it is observed in Fig. 4.3b, bottom, that the first arrival of the 'higher' frequency wavelet components seem to coincide with the arrival of the actual extensional mode. Therefore, any of these wavelet

Arnab Gupta

modes can be used to detect the arrival of the extensional mode. We choose the wavelet component with the highest amplitude, which is centered around 310 kHz, and use this waveform as a parameter to identify the time position where its amplitude first becomes a non-negligible value.



(b) Magnified segment of the same waveform shown above, focusing on the portion where the two wave modes arrive.

Figure 4.6. Waveform to determine the arrival of the extensional mode. Since each 'higher frequency' decomposition in Fig. 4.3b (bottom) indicates this arrival reliably, any one of those components can be used. The actual arrival times, identical to those in Fig. 4.3a, are indicated by red (extensional) and black (flexural) dashed vertical lines.

This can be seen in Fig. 4.6, where the wavelet decomposition centered around 310 kHz is shown, along with the actual arrival times of the extensional and flexural modes. Figure 4.6a shows the full waveform, while Fig. 4.6b focuses only on that segment

of the waveform that contains the time positions of actual arrival of the two wave modes. It is evident that the first non-negligible amplitude of the wavelet waveform coincides perfectly with the arrival of the extensional mode. Therefore, the first non-negligible peak in the waveform is used to identify the arrival of the extensional mode.

At the same time, it is evident that this waveform is not a good indicator for the arrival of the flexural waveform. Therefore, we must identify a different parameter that provides a similar easily-identified marker to identify the flexural wave mode.

4.4.2 Arrival of Flexural Mode

It is observed in Fig. 4.3b, middle, that the actual arrival of the flexural wave mode, marked by the black dashed line, does not seem to coincide in an obvious way with any of the wavelet components in view. From analysis of numerous ultrasonic signals with different amplitudes and signal features, it is observed that the actual arrival of the flexural wave mode coincides with the first peak in a wavelet component after the appearance of the small extensional component. This is in contrast with Section 4.4.1 where the identification parameter was first arrival, not the peak. However, it is also observed that this 'first peak' may appear in any one of the wavelet components classifies as being 'lower' frequency.

Therefore, to identify a parameter that reliably indicates the arrival of the flexural mode, we find the element-wise product of all of the wavelet components that we identify as 'lower' frequency. Mathematically this parameter q is given by:

$$q_i = \prod_j \omega_{ji} \tag{4.4}$$

where

 The set *j* denotes those wavelet decomposition components that are categorized as belonging to 'lower' frequencies. ω_j is the *j*-th wavelet decomposition of this set.



- (c) The same segment of signal as above, magnified further to show that the peak identified is the first significant peak, not simply the first non-negligible one.
- **Figure 4.7.** Waveform used to determine arrival of flexural mode. This is a product of each of the wavelet decompositions in Fig. 4.3b (middle). The actual arrival times, identical to those in Fig. 4.3a, are indicated by red (extensional) and black (flexural) dashed vertical lines.

In our case, the set *j* comprises wavelet decompositions centered around 70 kHz, 120 kHz, 170 kHz, 220 kHz and 270 kHz.

- *ω_{ji}* is the *i*-th element of the wavelet decomposition vector, where the total number of elements equals the length of the original signal.
- *q_i* is the *i*-th element-wise product of the vector *q* which is used as parameter to identify the arrival of the flexural mode.

The resultant waveform q is shown in Fig. 4.7, where Fig. 4.7a shows the entire waveform equalling the length of the original signal, and Fig. 4.7b focuses on the time portion that includes the actual arrival of the extensional and flexural modes. It is observed in Fig. 4.7b that with this parameter q, the actual arrival of the flexural mode indicated by the black dashed line coincides perfectly with the first large peak in the vector. Figure 4.7c magnifies the same portion of the signal further, whereby it is clear, from the presence of several minor peaks, that the coinciding peak is not simply the first non-negligible peak, but the first major one. Therefore, the appearance of the first large peak in the calculated parameter q can be taken as indication of the arrival of the flexural mode. This is in contrast from the case of the extensional mode where the first non-negligible peak was the identifying feature.

4.4.3 Peak and Prominence of Waveforms

In every algorithm to find the arrival of different wave modes, we must eventually find a way to identify either (a) a change in amplitude, using a threshold value, or (b) a local 'peak' value, i.e. where the waveform in question reaches a crest, or a trough, or either. Using either method has its disadvantages. When using a threshold value, the choice of threshold becomes important, and the reliability of the algorithm may depend on
Arnab Gupta

the probability of random noise to have a spike greater than the set threshold. When identifying local peaks, the difficulty is in identifying the 'correct' peaks, i.e. peaks due to signal amplitude rather than due to noise. After all, random noise also shows peaks and troughs, however small, and any method to find peaks in a signal will catch those due to noise too.



Figure 4.8. Relevant height measures needed to calculate the prominence parameter for two peaks in a sample curve.

A better method for such applications is to combine the two approaches. In this approach, each peak is weighted by a 'prominence' value, which helps magnify the critical peaks associated with signal content, and minimizes smaller peaks due to noise. The prominence p of a peak is given by the minimum height from the peak to the nearest trough on either side of the peak. If the signal ends before reaching a trough, the height to the last signal element is used for comparison. An example is shown in Fig. 4.8, where the relevant measurements of interest are shown for two peaks P_1 and P_2 . For P_1 , the prominence is given by $p = \min(h_{1L}, h_{1R}) = h_{1L}$, where the min() function returns the

lowest of its arguments. For P_2 , the prominence is given by $p = \min(h_{2L}, h_{2R}) = h_{2R}$. Visually we can ascertain that $h_{2R} > h_{1L}$; therefore, we can say that P_2 is a more prominent peak than P_1 .

In finding changes in waveform amplitude to identify the arrival of wave modes, we must identify all peaks in the waveform, and then particularly identify those peaks that signify the waveforms arriving. In doing so, instead of using the peaks themselves (i.e. the amplitudes of the peaks) for comparison with a threshold, we compare weighted values of the peak amplitudes. In our example of Fig. 4.8, instead of comparing the amplitudes a_1 and a_2 , we instead compare $a_1 \times h_{1L}$ and $a_2 \times h_{2R}$. This has the effect of automatically amplifying the peaks of importance, and diminishing the peaks due to noise and otherwise 'non-prominent' peaks.

Therefore, the algorithm to find the arrival of the extensional and flexural wave modes is as follows:

- Identify all of the crests and troughs in the applicable test waveform. With AE signals, 'peaks' may occur in both positive and negative amplitude directions, therefore both crests and troughs are of importance.
- Compute the prominence *p* of each peak identified, as described above.
- Create the parameter vector $m_i = a_i \times p_i$, where a_i and p_i are the amplitude and prominence of the *i*-th peak. This is the parameter that will be actually tested to identify the arrival of the wave modes.
- Analyze the parameter vector *m* to automatically identify appropriate threshold levels to identify the arrival of extensional and flexural modes. For the extensional mode, where the first non-negligible amplitude is to be found, the threshold level is determined based on an estimation of the noise level of the initial portion of the

m vector. For the flexural mode, where the first major peak is to be identified, the appropriate threshold value is determined based on how the amplitude properties of the vector change over its length.

• Test the parameter vector *m* against the threshold values identified in the previous step to identify the time position along the length of the vector when the two wave modes arrive. These positions or vector index numbers are the output, which can be converted to the appropriate time scale.

The algorithm presented here reliably identifies the signal features that it aims to identify. If, in some cases, the arrival times that the algorithm identifies seem to be slightly different than what is visually observed, then one of the following is true: (a) the two wave modes superpose in such a way that it is not apparent visually from the resultant wave where the actual arrivals occur, or (b) the underlying assumption of which wavelet components carry the two wave modes needs modification.

Figures 4.9 and 4.10 show a variety of ultrasonic signals for which the arrival times have been identified using the algorithm described in this article, implemented in MATLAB software. In all examples, the red dashed line represents arrival of the extensional mode, and the black dashed line represents the arrival of the flexural mode. It can be seen in Fig. 4.9 that even for signals with different noise levels, the two wave modes are reliably identified. In Fig. 4.10, it can be seen that identification of the two wave modes occurs accurately for PLB signals with different peak amplitudes and wave shapes (corresponding to attenuation due to distance of the source from the signal).

4.4.4 **Programming and Performance**

The process presented here is implemented using MATLAB software. Custom scripts are used to achieve all relevant tasks, including finding the peaks and troughs, and their



Figure 4.9. Representative signals from natural Acoustic Emission events, and algorithmically identified arrival times of their extensional (red dashed vertical line) and flexural (black dashed vertical line) modes.



Figure 4.10. Representative signals from Pencil Lead Breaks, and algorithmically identified arrival times of their extensional (red dashed vertical line) and flexural (black dashed vertical line) modes.

prominence values, from an input waveform, finding relevant threshold values to use for flexural mode arrival, and finally to analyze and identify the arrival of the extensional and flexural modes. These scripts require no input other than the test waveforms, and all noise and threshold estimations are performed automatically. A minimum value for noise is prescribed, and this should not need to be modified under most circumstances.

The developed MATLAB scripts were run on a MacBook Pro notebook computer running MATLAB R2017a, reading and writing data files over a USB3.0 connection to an external spinning disk hard drive. Using this configuration, the arrival times of both extensional and flexural wave modes were calculated from previously computed wavelet transform data at a rate of \approx 40s per 1000 signals. Without considering the time to read from and write to disk, executing the scripts using wavelet data already imported into MATLAB requires \approx 3.5s per 1000 iterations of calculating both extensional flexural arrival times.

The MATLAB scripts developed have been made available as a Mathworks File Exchange repository [web, e], as well as in a public repository hosted at BitBucket.org [web, h]. Both repositories include all required MATLAB scripts, along with example MATLAB code and accompanying example data.

4.5 Summary

The wavelet decomposition of ultrasonic signals is used to identify when extensional and flexural wave modes arrive. For identifying each wave mode, a suitable waveform is identified that can be used for further analysis. For the extensional wave mode, a wavelet decomposition centered around a reasonably high frequency (310 kHz in our case) is used, while for the flexural mode, several wavelet components centered around lower frequencies are multiplied together to create a new waveform.

In order to find the peaks from the test waveforms that indicate the arrival of wave modes, the prominence of each peak in the waveform is calculated, and is used to create a new parameter *m* that naturally amplifies the most prominent peaks and diminishes the least prominent ones. This parameter is analyzed to automatically determine appropriate threshold values, which are then used to identify the arrival of wave modes.

The algorithm presented here can be implemented in an automated manner to identify the arrival of extensional and flexural wave modes in a large number of acquired signals using wavelet transform data. The algorithm is easily fine-tuned to work with signals involving different materials and applications, by choosing the wavelet components that form the basis of the test waveforms.

Declarations

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Chapter 5

Early Detection of Critical Damage

Publication Information

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5.1 Abstract

Composite materials are in increasing use in practical engineering applications, where it is crucial to be able to anticipate future failure of the components. Without such knowledge, components must be removed from service at a statistically safe service life, which leads to wasted performance from perfectly healthy components. This article proposes a method

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to monitor composite specimens over their service life, and observe the variation of certain parameters that provide an early indication of future failure of the specimen. Pencil Lead Breaks are used as a source of simulated AE waves that are acquired by two piezoelectric ultrasonic sensors. Composite specimens of different ply layups are subjected to slowspeed cyclic loading until failure, and Pencil Lead Breaks are performed at pre-determined locations on the specimen periodically throughout the experiment. The energy of the signals as acquired by both ultrasonic sensors is compared, both in terms of the total signal energy, as well as in terms of wavelet component contributions. The ratio of energy contributions allows the early detection of future failure in specimens of varied ply-layups, and allows detection early enough in the specimen's life to plan effective maintenance strategies.

Keywords: Health Monitoring; Composite Materials; Pencil Lead Break; Wavelet Analysis; Acoustic Emission; Data Analysis

5.2 Introduction

In practical engineering applications of composite components, it is of fundamental importance to have a reliable understanding of the health state of the components in service. This understanding must include knowledge of expected failure of the component, or at least, a method to anticipate upcoming failure, beyond purely statistical inferences. In metallic materials, component deterioration proceeds in the form of a small number of cracks [Plumbridge, 1972, Carpinteri, 2012, Pearson, 1975]. The size and evolution of these few cracks, usually occurring in areas of high stress-concentration which can be pre-identified, and their growth rates can be reliably used to anticipate future failure of the component. In contrast, failure in composite materials proceeds in a very different manner than in metallic materials.

Composite components undergo deterioration through several mechanisms such as fiber breaks, matrix cracks and delaminations [Proctor et al., 1983, Garg and Ishai, 1985, Bhat et al., 1994, Yoji et al., 2010]. These modes of deterioration are precipitated by not only the loading regime and component geometry, but also factors such as the fiber orientation in different layers, the nature of the localized bonding between fibers and the matrix, moisture and temperature during operation, and the distribution of strength and stiffness among all the fibers that the component contains. Numerous small, insignificant deterioration events occur throughout the life of the component, that have negligible effect on the service life of the component, but which make it difficult to employ similar health monitoring schemes as used for metallic materials [Reifsnider and Talug, 1980]. Towards the latter stages of the component's life, damage events in the very same modes will have a more drastic effect on the performance of the component, and culminate in ultimate failure. In composite components, it is crucial to be able to identify characteristics of the component that indicate that such drastic damage events are occurring which may lead to future failure.

One of the major methods to study composite materials is by utilizing acoustic ultrasonic waves traveling within the material [Scruby, 1987, Fleischmann et al., 1975, Prosser and Gorman, 1994]. Acoustic ultrasonic stress waves, known as Acoustic Emission (AE) waves, are generated in a component every time a localized stress redistribution event occurs, i.e. any time a deterioration event occurs within a component. Such waves can also be generated artificially by simulating a stress redistribution, by subjecting the specimen to a small point load and then suddenly removing the load. This load removal simulates a load redistribution like a deterioration event, and generates simulated AE waves within the component.

The acoustic stress waves traveling through a material can be acquired by installed piezoelectric ultrasonic sensors. The acoustic waves are affected by the properties of the

path through which they travel, and therefore the signal acquired by multiple sensors reflects the health state of the material along the particular path traveled by the acoustic wave. As the health state of the material changes, it may affect the traveling acoustic wave differently, and this variation may be discernible in the acquired signals.

Detection of damage in composite materials is an active area of research. However, much of the focus is in detecting the presence of specific damage, and their location, in composite specimens [Toyama et al., 2003a, Kessler et al., 2002, Toyama et al., 2002]. However, identifying precursor indicators that help in predicting upcoming component failure is of more importance than the identification and localization of any particular damage event in composite components. This article proposes a method and specific parameters to monitor composite specimens over its service life using simulated Acoustic Emission and to enable early detection of upcoming specimen failure.

5.3 Background

5.3.1 Pencil Lead Breaks

Even though AE waves are generated in a specimen under load every time a deterioration event occurs, they present a challenge in attempting to identify changes in acquired signal data to understand the evolving health state of the component. First, the location of the events that generate the AE waves are distributed throughout the specimen. Therefore, the path and distance of the waves from the sensors that acquires the signals is different for every deterioration event. Second, where the objective is to identify changes in signal characteristics, the very nature of the AE waves may be different between different deterioration events. Therefore, property changes in signals that are acquired cannot be definitely attributed to changing health state of the component. The way around this conundrum, of course, is to utilize simulated AE waves. In experimental research, Pencil Lead Breaks (PLBs) — also known as the Hsu-Nielsen source [Hsu and Breckenridge, 1981] — have long been used for this purpose [Gary and Hamstad, 1994, Sause, 2011, Hamstad, 1982, Boczar and Lorenc, 2004], where a mechanical pencil with a length of lead extended is pressed on the surface of the specimen at a specific location, and then pushed down until the extended pencil lead breaks. This process subjects the specimen to a small point load that is suddenly removed, providing the source for the generation of simulated AE waves. PLBs satisfy the criterion of generating acoustic waves that are wideband, i.e. the waves span a wide frequency range. This is important because waves of different frequencies may travel differently through the composite specimen, either in general, or even differently at different stages of life of the specimen.

PLBs can be performed at particular locations on the specimen under scrutiny, which means that the path of the acoustic waves to the sensors is always nominally the same. If different wave-paths are desired, PLBs can simply be performed at multiple locations as needed. PLBs also have the advantage of providing a steady, unchanging source of simulated AE waves throughout the life of the specimen. Since it is known that the nature of the acoustic waves generated by the PLBs themselves is nominally constant, any changes observes in the acquired signals can be safely attributed to changing health state of the specimen.

5.3.2 Wavelet Analysis and Signal Energy

In analyzing acquired experimental signals, the most fundamental question is the composition of the signals in terms of (a) frequency content and (b) when in time these different frequency components arrive at the sensor. Any subsequent analysis and inference about the signals can proceed from this fundamental information. Wavelet Analysis [Mallat, 2008] is an excellent method to decompose signals into their frequency and temporal components [Mallat, 1989, Vetterli and Herley, 1992].

The Wavelet Transform is conceptually similar to the Fourier Transform [Suzuki et al., 1996, Serrano and Fabio, 1996]. The Fourier Transform uses a series of sine and cosine functions as reference to correlate with the signal being tested, and returns as its result the frequencies where it finds a match. However, since the sine and cosine functions are independent of time, the Fourier Transform provides no information about the temporal aspects of the matched frequencies. The windowed Fourier Transform is an attempt at a workaround, but the constant width of the window means that any component with a wavelength larger than the window width cannot be detected.

The Wavelet Transform also uses a reference function, but unlike the Fourier Transform, this reference function can be chosen from among many options based on the particular application. The reference function, called the 'mother wavelet', is not an 'infinite' wave like the sine and cosine waves (notice the name wave-*let*), but is transient and only has non-zero values over a small time range. The Wavelet Transform matches the mother wavelet with different frequency components and time segments of the signal being analyzed by [Vetterli and Herley, 1992] (a) translation over various time segments of the signal, and (b) dilation and compression to match various frequencies. The Wavelet Transform is thus able to discriminate signal components across both the time and frequency axes. Perrier et al. [Perrier et al., 1995] describes the mathematical differences between Fourier spectra and Wavelet spectra.

For analysis of transient signals — such as short-lived acoustic waves in our case — the Continuous Wavelet Transform (CWT) in particular performs well [Tang et al., 2011], and is given by:

$$X_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t) \overline{\psi}\left(\frac{t-b}{a}\right) dt$$
(5.1)

where

- *x*(*t*) is the input signal as a function of time
- ψ(t) is the particular mother wavelet used, and must be continous both in the time and frequency domains. ψ(t) denotes the complex conjugate of ψ(t).
- *a* (>0) is called the "scale factor", and either dilates or compresses the mother wavelet.
 The scale factor can be converted to an equivalent set of frequency values.
- *b* is the "translational factor", and moves the mother wavelet along the time axis.
- *X_w(a, b)* is the resultant output of the wavelet transform, and provides two-dimensional data corresponding to (*a, b*) values.

There are many choices for the 'mother wavelet', and the Morlet Wavelet in particular is known to work well with transient signals [Shyu and Sun, 2002]. We use the real-valued Morlet Wavelet (Fig. 5.1), given by:

$$\psi(t) = \exp\left(\frac{-t^2}{2}\right) \cdot \cos 5t \tag{5.2}$$

The wavelet scale factors a are related to equivalent frequency values f_a by:

$$f_a = \frac{f_c}{a \cdot t} = \frac{f_c \cdot f_s}{a} \tag{5.3}$$

where

• f_c is the center frequency of the mother wavelet. In Eq. (5.2), it is evident that the Morlet wavelet reduces to $\cos 5t$ when t = 0, which means that the center frequency

of the wavelet should be $\frac{5}{2\pi}$ Hz. This can be confirmed by comparing the Morlet wavelet with a sinusoidal wave of frequency $\frac{5}{2\pi}$ i.e. ≈ 0.7958 Hz, and observing (Fig. 5.1b) that the sinusoidal wave matches perfectly the center of the wavelet.

- *a* is the scale value being converted.
- *t* is the time period of sampling, i.e. the time duration between acquisition of consecutive data samples.
- f_s is the sampling frequency, i.e. number of times per second data is acquired. Evidently, $f_s = 1/t$.
- f_a is the frequency value corresponding to the scale value a.



Figure 5.1. The solid blue curve in both figures shows the real-valued Morlet wavelet. In Fig. 5.1b the dashed red curve shows the sinusoidal wave that perfectly matches the center of the wavelet, having a frequency of ≈ 0.7958 Hz.

The output of the Wavelet Transform is a matrix of wavelet coefficients, correlating to the contribution of the signal at specific *(time, scale)* pairs. Along one dimension, the matrix is of the same length as the time length of the signal. Along the second dimension, the matrix has as many elements as the number of scale values specified. Therefore, for

a signal with *n* data points, and a wavelet transform with *s* scale values, the output is a matrix of wavelet coefficients of size $s \times n$.

The wavelet coefficients provide an estimation of the signal components corresponding to each scale value. The signal components are never constrained exactly by the equivalent frequencies of the scale values; the signal components will rather be 'centered around' the equivalent frequencies. For each scale value, the vector along the time dimension correlates to the signal contribution centered around the equivalent frequency. The coefficients are only significant relative to other coefficients of the same wavelet decomposition; it is meaningless to compare the wavelet coefficients of different signals by their absolute values only.

However, the wavelet coefficients can be used as a measure of signal energy distribution. Since the square magnitude of a Fourier- or wavelet-type coefficient is proportional to local energy [Shyu and Sun, 2002], the squared values of the wavelet coefficients can be used to indicate the distribution of energy in the signal. It must be noted that this process does not show the total energy in the signal, only the energy distribution at different frequency and time points. This energy distribution can be computed using the following:

$$S_{ij} = w_{ij} \times w_{ij} \quad \forall i, j \tag{5.4}$$

$$SC_{ij} = 100 \times \frac{S_{ij}}{\sum_i \sum_j S_{ij}}$$
(5.5)

where

- w_{ij} is the wavelet coefficient corresponding to the matrix position (i, j)
- $(SC)_{ij}$ is the energy contribution at the same (i, j) position

In the first step (Eq. (5.4)) each wavelet coefficient is multiplied by itself to create

an intermediate matrix of values S_{ij} . In the next step (Eq. (5.5)), these intermediate values are converted to energy proportions by normalizing each element by the total sum of all elements of S_{ij} . The result is the matrix SC of the same dimensions as the original wavelet coefficients. Here 'SC' stands for Scalogram, which is a visual representation of this exact energy proportion.

The total energy content of a signal can also be calculated directly from the acquired signal by taking the square of the amplitude at each data point [Stoica et al., 2005]. In this case, the result is a single number that indicates the total energy of the signal. Mathematically, this operation is given by:

$$E = \sum_{t} x^2(t) \tag{5.6}$$

where x(t) is the acquired signal amplitude as a function of time t, and E is the calculated total energy.

5.4 Method

5.4.1 Experiments

Experiments are performed with rectangular coupons (dimensions: $300 \text{ mm} \times 25 \text{ mm}$) machined from composite laminates (dimensions: $300 \text{ mm} \times 300 \text{ mm}$) of various ply layups. The laminates are prepared in-house by hand layup and subsequent curing under heat and pressure of plies from a pre-impregnated material (5245C) with unidirectional carbon fibers (G40-600). The ply layups of the coupons used were: (a) $[0^{\circ}/90^{\circ}_{3}]_{S}$, (b) $[0^{\circ}/\pm 60^{\circ}]_{S}$, and (c) $[90^{\circ}/\mp 30^{\circ}]_{S}$, where the 0° direction is along the length of each coupon. Figure 5.2 shows a schematic of an experimental coupon setup for an experiment.

Two piezoelectric ultrasonic sensors, specifically model SE1000-H manufactured by



Figure 5.2. Schematic showing experimental sample with piezoelectric sensors attached. Locations marked (a) and (b) indicate locations where Pencil Lead Breaks are performed. Blue circles represent locations where piezoelectric sensors are attached.

Score-Atlanta [web, a], are used for data acquisition, and have an active region $\approx 2 \text{ mm}$ in diameter (a schematic is shown in Fig. 5.3). The sensors are held securely to each specimen at predetermined locations, using rubber bands and simple wood supports. A silicone based grease-like lubricant [web, d, web, b] is applied to the active surface of the sensors before installation for optimum contact and consistent transfer of mechanical waves between the sensor and the specimen. The sensors are held securely enough to ensure consistent contact with the specimen as well as avoid sliding during the experiment. The position of the sensors is outlined using permanent marker during experiments, and numerous observations over multiple experiments confirm that the sensors do not slide over the course of an experiment. The fixed orientation of the wood supports also ensures that the sensors are always oriented in the same manner when they are set up for an experiment and for the duration of the experiment. If Fig. 5.2, the large blue circles represent the piezoelectric sensors.

For data acquisition a dedicated circuit board, installed in a Windows PC, and its associated software package is used. The circuit board has two data input channels into which output from the two piezoelectric ultrasonic sensors are fed. The software includes a circular buffer and is set to save data that arrives both before and after a triggered event. One of the two piezoelectric sensors is used as trigger, and data is saved every time the signal from this sensor rises above a minimal threshold. The use of the circular buffer is



Figure 5.3. Piezoelectric Sensor and its direction of sensitivity

crucial for multi-sensor data acquisition. In the case when the acoustic wave source is farther from the trigger sensor than the non-trigger sensor, the traveling wave reaches the non-trigger sensor before data acquisition has been triggered. Therefore, in order to capture the full signal received by the non-trigger sensor, data must be captured from before the wave reaches the trigger sensor. Data is collected at 25 MHz, with 3072 data points saved before the trigger activates and 7168 data points saved afterwards, for a total of 10240 data points over 409.6 µs.

An MTS screw-driven electro-mechanical Universal Testing Machine [web, g] is employed for mechanically loading the specimens. The specimens are loaded under a slow speed tensile-tensile cyclic condition until they undergo failure under fatigue. The machine is programmed to operate between specified upper and lower load limits and a constant velocity for a specified number of cycles. The load limits and the loading rate are decided based upon the expected strength of the coupon; for example, a coupon with layup $[0^{\circ}/90^{\circ}_{3}]_{S}$, with fibers along 0° , is expected to be stronger and require a higher load to undergo deterioration than a coupon with layup $[90^{\circ}/\mp 30^{\circ}]_{S}$, with no fibers along the 0° direction. For nominally stronger specimens, a loading rate of 40 mm min⁻¹ between load limits of 10 kN to 32 kN is typical. For weaker specimens, a speed of 25 mm min⁻¹ and loading limits of 3 kN to 12 kN is more typical. The parameters may differ slightly between specimens depending on how the particular specimen in perceived to be behaving.

For each specimen, the experiment is started gently with lower values of upper load limit and loading rate, to avoid the specimen undergoing catastrophic damage during first loading. Gradually, the loading limits and loading rate are increased to the intended levels. Since even a 'high' loading rate translates to very low frequencies, the experiments are run in low-cycle regimes, with specimens intended to have relatively short lives of < 15000 cycles to failure.

5.4.2 Pencil Lead Breaks

Pencil Lead Breaks (PLBs) are performed at the beginning of the experiment as well as throughout the experiment at regular intervals. For the present study, PLBs are performed at two pre-determined locations along the center-line of the specimen (green circles marked (a) and (b) in Fig. 5.2).

A mechanical pencil equipped with 2H pencil lead is used to perform Pencil Lead Breaks. The lead is extended from the mechanical pencil by a fixed amount (\approx 3 mm), after which the pencil is pressed manually against the specimen at a consistent angle (\approx 45°) so that the point under the pencil is under compressive load. When the pencil is pressed sufficiently, the pencil lead breaks, thereby releasing the compressive load suddenly. This impulse release of load generates the simulated AE-type stress waves in the specimen. For consistent generation of acoustic waves, the position and angle of the pencil must be kept nominally consistent, as changing these parameters can cause differences in the energy imparted to the specimen (Fig. 5.4). Towards the end of a specimen's life, deterioration in the health state of the specimen may attenuate the acoustic waves and impede their detection by sensors that are farther away. In this case, the energy of the PLBs is increased by making the angle of the PLB steeper (Fig. 5.4b), so as to enable satisfactory



data acquisition by both sensors.

(a) PLB at a shallow angle of incidence. Pencil lead can only sustain a small load and breaks very easily.





Figure 5.4. Performing a Pencil Lead Break at different angles of incidence θ

PLBs are performed before first loading each specimen, as well as every 200 cycles. Initially when the loading rate and speed are still being gradually increased, PLBs are performed every 100 cycles. When a set of PLBs is performed, the cyclic loading is paused and the load is held steady at the lower load limit. A set of PLBs comprises at least 4 PLBs at each location for redundancy. This way, even if a single PLB is administered incorrectly, or the location of the PLB is inaccurate by a minute amount, the presence of multiple PLBs ensures the integrity of the collected data as a whole.

For this study, the energy content of acoustic waves over the life of specimens will be compared and analyzed. Therefore, PLB signals are exclusively used for this study, for the reasons described in detail in Section 5.3.1.

5.4.3 Wavelet Analysis

A wavelet transform using the real-valued Morlet wavelet is performed on all signals. The scale values for this transform should be chosen so that the equivalent frequencies as given in Eq. (5.3) are spread over the entire spectrum where the sensor is expected to be

sensitive. The frequencies chosen for this current work are, in kHz, 60, 100, 160, 220, 260, 300, 360, 430, 480, and 530 (total 10), which are converted to the equivalent scale values using Eq. (5.3). The choice of these particular frequencies is informed by previous analysis where the frequency spectra of acquired signals shows peaks in the neighbourhood of the above-chosen frequencies. Figure 5.5 shows the normalized amplitudes of a Fast-Fourier Transform (FFT), of each frequency component, of the wavelet transform of a representative acoustic wave signal. It is evident that the peaks correspond, in kHz, to 60, 100, 160, 220, 300, 360 and 430. The higher frequencies — 480 kHz and 530 kHz — are chosen so as to nominally cover the frequency regions that the sensors may possibly be sensitive to.



Figure 5.5. To observe the contribution of different frequency components, an FFT is performed on each frequency component of the wavelet transform of a representative acoustic signal. The amplitudes are normalized and plotted, which clearly shows the relative peaks along the frequency axis. Lines of each different color correspond to a different frequency component.

The energy distribution in each wavelet decomposition is also calculated for each signal using Eq. (5.5). This wavelet energy distribution is of interest to us, and we want to analyze how this energy distribution evolves over the life of various specimens. However, in performing such analysis, the resolution along the time axis is too high for productive

comparison. This is because of two reasons. First, with a sampling frequency of 25 MHz, each data point along the time axis is separated by only 40 ns, and even the most random variation in signal transmission within the material can cause variations at such a small time scale. Second, with such a high time resolution, the contribution at each time instant is very very small, and variations are hard to identify with such small numbers. Therefore, the energy distribution values are consolidated along the time axis. Since the total energy in the entire signal totals to 100%, we sum the contributions of adjacent time points such that a smaller energy distribution matrix is obtained. This consolidation is performed so that the time axis is divided into 40 segments, with each segment comprising $\approx 10 \,\mu s$. Dividing the time axis into 40 segments is determined to be a good balance between capturing important variation details, while also keeping the contribution from each time segment significant. The energy distribution matrix SC is now updated into the new energy distribution SC₄₀.

5.4.4 Energy Peaks and Energy Ratios

With the objective of analyzing the variation in energy distribution of PLB signals, we realize that comparison of entire SC_{40} matrices for numerous PLB signals is cumbersome and impractical. Instead, we need to select specific parameters from each SC_{40} matrix which will allow us to perform our analysis efficiently. We choose as our parameter the peak value of energy corresponding each wavelet (frequency) component. Therefore, for each PLB signal, the peak value corresponding to each of the 10 frequency components mentioned in Section 5.4.3 is identified and saved.

Now, in analyzing the variation in these identified peak values, we postulate that any change over the life of each specimen will be best observed by comparing the energy peaks as received by both ultrasonic sensors due to the same PLBs. The reasons for this contention are as follows. First, for the same PLB, using data from both sensors provides a better indication of the overall health state of the specimen, since the same acoustic wave travels through more of the specimen material in reaching both sensors than in reaching a single sensor. Second, using the ratio of peaks compensates for some of the variability that may arise from even minute variations in PLB position and total energy content. For example, if two successive PLBs have different acoustic wave energies, this variation will be similarly reflected in signals from both sensors, and the energy ratio will maintain better consistency than either single energy value.

For each PLB signal and each frequency component therein, the peak values as acquired by the two sensors is compared, and their ratio is calculated. In addition to comparing the peak values from the energy distributions, we would also like to compare the total energy in the PLB signals. For this, we make use of the total signal energy computed directly from the acquired signal, as described in Section 5.3.2. Once again, we postulate that variations will be best observed by comparing the total energy as acquired by both sensors, and we calculate the energy ratio.

5.5 Results

For each PLB signal, we plot the variation in energy ratio of different wavelet components, as well as the energy ratio of the total signal energy. In calculating the energy ratios, the contribution from the sensor nearer to the PLB location is kept in the numerator, so that the calculated ratio is always positive. (The energy of the signal acquired always attenuates with distance from the source.) Since PLBs are performed at two locations, as shown in Fig. 5.2, two sets of data are plotted for each specimen.

As mentioned in Section 5.4.2, whenever PLBs are performed during each experiment, several PLBs are performed (let's call them 'groups' of PLBs) at each location to Arnab Gupta

maintain data reliability and to account for any random variations. When plotting data, we plot the median energy ratio values for each group of PLBs. The median value is chosen in preference over the mean because the energy ratios are expected to be consistent within any single group of PLBs, and therefore the 'central' value is more useful than incorporating the contribution of 'outliers'. The energy ratio values are also normalized to span a range of 0 to 1. Since the calculated energy ratios are never < 1, the following equation is used for normalization:

$$E_n = \frac{E - \min(E)}{\max(E)}$$
(5.7)

where *E* is the set of energy ratio median values under consideration, min(E) and max(E) are the minimum and maximum values, and E_n the normalized set of values ranging from 0 to 1.

Figures are presented for representative specimens with different ply layups, viz. $[0^{\circ}/90^{\circ}_{3}]_{S}$, $[0^{\circ}/\pm 60^{\circ}]_{S}$, and $[90^{\circ}/\mp 30^{\circ}]_{S}$, as mentioned in Section 5.4.1. Specimens with different ply-layups undergo deterioration through different damage mechanisms, and different modes of deterioration may play principal roles. Therefore, we are interested to observe if a consistent set of parameters can be effective in identifying future failure in specimens with several different ply layups, including ones without 0° fibers present.

For each specimen, we would like to observe the variation in energy ratios for the total energy content in the signal, and each of the 10 frequency components. For the frequency components, since it is cumbersome to visualize so many individual components, we choose to focus on a few specific wavelet frequency components. It is observed in Fig. 5.5 that the frequency components do have overlaps, and based on this knowledge and observation of numerous signals, we select the following components: (a) centered around 100 kHz representing 'lower' frequencies, (b) centered around 360 kHz and 430 kHz rep-

resenting 'higher' frequencies, and (c) centered around 220 kHz representing the 'middle' frequencies.

Specimens under cyclic loading fail at different numbers of cycles, and therefore also have different numbers of PLBs performed on them. To be able to effectively compare the variation in energy ratios over the life of the specimen, a 'stage of life' parameter must be computed. For each specimen, the number of cycles at which each group of PLBs is performed is normalized against the total number of cycles after which specimen failure occurred. This 'percentage of life' scale is used to calibrate the location of each group of PLBs in terms of the 'stage of life' of the specimen.

The nature and constraints of our experimental loading regime may affect the stage of life of a specimen at which important changes in energy ratio are observed. Since our specimens were loaded such that they would fail at relatively low fatigue cycles (< 15000 cycles), our loading limits were set higher than they would in practical service scenarios. Consequently, in some specimens, major deterioration may occur relatively early in the life of the specimen. In practical service scenarios, the specimen would be expected to be removed from service beyond such deterioration, even though the specimen does not immediately fail catastrophically, and our experiment proceeds until the specimen does fail. Additionally, although acoustic waves from both sets of PLBs should travel through nominally the same straight line between the two sensors, practically there may be small differences between the wave paths for the two data sets. Therefore, variations in energy ratio may appear at slightly different stages of a specimen's life, as even adjacent segments of the specimen undergo deterioration differently.

Figures 5.6 to 5.13 show the variation in energy ratio for a number of specimens of different ply layups. In each figure, the two colors represent two sets of PLBs performed at two different locations (Fig. 5.2) on each specimen. In each figure, sub-figure (a) shows the ratio of the total signal energy. Sub-figures (b), (c) and (d) show the ratio of the

wavelet component peaks corresponding to 'lower' frequency, 'higher' frequencies, and 'middle' frequency, respectively. Each figure also shows vertical dashed lines (one or more) corresponding to observed major changes in the energy ratio. The vertical lines are drawn at the same 'percent life' position in all sub-figures for easy comparison.

Figures 5.6 to 5.9 show the energy ratio for specimens with a $[0^{\circ}/90^{\circ}_{3}]_{S}$ ply layup. Figures 5.10 and 5.11 show the energy ratio for specimens with a $[0^{\circ}/\pm 60^{\circ}]_{S}$ ply layup, and Figs. 5.12 and 5.13 shows specimens with a $[90^{\circ}/\mp 30^{\circ}]_{S}$ ply layup. In specimens with different ply layups, there are no distinct characteristics observed in the plotted energy ratios that appear to correspond to only particular ply layups. The characteristics observed are consistent between specimens of all the ply-layups.

In all specimens, there is usually a change in energy ratio right at the beginning of the experiment. This is expected: as the specimen in first loaded, small deterioration events always occurs before the specimen 'settles down' to its service regime. These initial events occur in those portions of the specimen that are weaker statistically than the specimen as a whole, and this initial deterioration does not affect the service life of the specimen. In the remainder of the specimen's life, every specimen shows at least one major change in the energy ratio in all plotted sub-figures, which indicates a major change in the health state of the specimen in the middle portion of the specimen's service life.

In Figs. 5.6 and 5.9, two distinct changes in energy ratio can be observed. In both specimens, the first such changes occurs relatively early in the specimen's life, while the second change occurs much later. It is evident that the changes can be observed both in the ratio of the total signal energy as well as in the wavelet components. It is also evident that the same changes are more pronounced from wavelet components than from total signal energy. For example, in Fig. 5.6, the first change is most evident in Figs. 5.6b and 5.6d, while the second change is most prominent in Figs. 5.6c and 5.6d. Similarly, in Fig. 5.9, while the first change is prominent in all sub-figures, the second change is most prominent

in Figs. 5.9c and 5.9d.

In Figs. 5.7, 5.11 and 5.13, two distinct changes are also observed, but in these cases, the changes appear with only a small percentage of specimen life elapsing between them. For these specimens, it may so be the case that the same deterioration process is responsible for both changes, but they appear at slightly different times in the two sets of PLBs. In Figs. 5.7a and 5.7d, the two sets of PLBs both appear to undergo major changes, but with a small offset in percent life. Figures 5.7b and 5.7c show simultaneous changes to both PLB sets, but it is evident that the deterioration or evolution completes only after the second of the observed changes.

In Figs. 5.8, 5.10 and 5.12, a single major change in the ratio of energy peaks is observed. In Fig. 5.8, all sub-figures show the change, although the extent of the observed change is varied amongst the different components and PLB sets. In Fig. 5.10, the changes are best observed in Figs. 5.10a, 5.10c and 5.10d, where both PLB sets show the change equally well. In Fig. 5.10b, however, only set of PLBs show the change, while the other undergoes a gradual change over a long fraction of the specimen's life without exhibiting any specific marked change.

As summary, we can say from observing results from all of the specimens that:

- all of the specimens show distinct changes in the ratio of peak energies between two ultrasonic signals.
- the extent of change may vary between different parameters being observed, but as a whole the change is always easily observed.
- although the ratio of total signal energy does show the changes, individual wavelet components show more distinct changes than the total signal energy. This makes sense: if the shift in energy contribution is confined to certain frequency components

and not others, the total combined effect on the total signal energy may be smaller than in the individual frequency components.

• using multiple locations for PLBs is better than using a single PLB source. This is because the wave path from different sources, even if they are only minutely different, may show up deterioration changes in adjacent segments of the specimen. Such minute differences may be important in terms of early detection of specimen health deterioration.

5.6 Conclusions

Composite coupons with different ply layups are subjected to slow-speed cyclic loading until the specimens undergo failure due to fatigue. During the experiments, Pencil Lead Breaks are performed at two pre-determined locations on the specimen to generate simulated AE ultrasonic waves that travel through the specimen. These waves are acquired by two piezoelectric ultrasonic sensors, and the captured signals are used to determine the energy ratio of different signal components in order to devise an early detection scheme to indicate future failure of the specimens.

By observing changes in the energy ratio in all of the specimens, we conclude that oncoming failure of composite components can be detected effectively with this method. Specifically, the ratio of total signal energy as acquired by multiple ultrasonic sensors can be used as an indicator. Alternatively, observing several frequency components of the signal wavelet decomposition also provides excellent results.

In calculating the energy ratios, either due to total signal energy or from the contribution of wavelet components, it is important to have as a baseline a signal that remains consistent in terms of frequency content and signal energy at the source. For



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.6. Energy Ratios for specimen 1, with ply-layup [0°/90°₃]_S. Blue and Red curves denote data from two different sets of PLBs.





(a) Ratio of total energy contained in acoustic waves

(b) Ratio of peak values of wavelet component centered around 100kHz (lower frequency)



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.7. Energy Ratios for specimen 2, with ply-layup $[0^{\circ}/90^{\circ}_{3}]_{S}$. Blue and Red curves denote data from two different sets of PLBs.



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.8. Energy Ratios for specimen 3, with ply-layup [0°/90°₃]_S. Blue and Red curves denote data from two different sets of PLBs.



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.9. Energy Ratios for specimen 4, with ply-layup [0°/90°₃]_S. Blue and Red curves denote data from two different sets of PLBs.



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.10. Energy Ratios for specimen 5, with ply-layup $[0^{\circ}/\pm 60^{\circ}]_S$. Blue and Red curves denote data from two different sets of PLBs.



(c) Ratio of peak values of wavelet component centered around 360kHz and 430kHz (higher frequency)

(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.11. Energy Ratios for specimen 6, with ply-layup $[0^{\circ}/\pm 60^{\circ}]_S$. Blue and Red curves denote data from two different sets of PLBs.









(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

Figure 5.12. Energy Ratios for specimen 7, with ply-layup $[90^\circ/\mp 30^\circ]_S$. Blue and Red curves denote data from two different sets of PLBs.




(d) Ratio of peak values of wavelet component centered around 220kHz (middle frequency)

40

Percent Life (%)

60

80

100



Figure 5.13. Energy Ratios for specimen 8, with ply-layup $[90^\circ/ \mp 30^\circ]_S$. Blue and Red curves denote data from two different sets of PLBs.

0.2

0

0

20

this purpose, simulated AE in the form of performed Pencil Lead Breaks performs well. However, for practical applications, this method can be adapted to create automated periodic point excitations that can create wide-band acoustic waves that travel within a component of interest. If automated, those signals can also be acquired and processed automatically.

The method presented in this article also shows that the indication of future failure occurs early enough in the life of a specimen that a maintenance operation can be planned if this method is used practically for component inspections. It is observed that even after the indicated change in energy ratio, specimens do not under immediate catastrophic failure; instead they continue to function under the same loading regime for some length of time. This is crucial in practical scenarios, where a maintenance operation may involve technicians traveling to remote locations to perform the necessary operations.

Chapter 6

Conclusions

6.1 Contributions of this dissertation

This dissertation makes the following contributions:

1. In Chapter 3, we show the effects of cumulative deterioration on cross-ply laminates, with ply layup $[0^{\circ}/90^{\circ}_{3}]_{S}$, under slow but monotonically increasing tensile loading. We show that signals acquired by installed piezoelectric sensors, by performing Pencil Lead Breaks at pre-determined locations on specimens, can be employed to gauge the health state of composite materials. We show that the difference in arrival times of the extensional and flexural wave modes shows marked changes towards the latter portion of a specimen's life.

We also perform a Wavelet Transform on the acquired signals, and show that the energy distribution over different frequencies and time regions of the acquired signals depend upon the signal attenuation that the traveling acoustic waves encounter. For example, when considering acoustic waves traveling along the fiber direction, we find that the signal energy distribution is very different at the beginning of a specimen's life than towards the end. On the other hand, if we consider the acoustic waves traveling at an angle to the fiber direction, and hence being attenuated more, then the energy distribution even at the beginning of the specimen's life resembles the distribution in the previous case at the end of the specimen's life.

Using the calculated Wavelet Transform of acquired signals, we observe the variation over specimen life of centroidal frequency value and total energy at each time instant. We show that these calculated parameters show a significant difference between the beginning and towards the end of specimen life. However, we also show that the parameters remain consistent over changing loads at the beginning of specimen life, as well as towards the end of specimen life, confirming that a fundamental change in material response occurs at a certain point in the specimen life, rather than a consistent gradual change from the beginning to the end of specimen life.

2. One of the essential steps in any health monitoring process for composite laminates is to identify from acquired ultrasonic signals the time of arrival of the extensional and flexural modes. If any automated health monitoring system is to be developed and deployed, there needs to be a fast and reliable method to estimate the arrival times of large sets of acquired ultrasonic signals, whether the source of the signals be natural Acoustic Emission activity or simulated by, for example, Pencil Lead Breaks. In Chapter 4, we develop a method to perform this task automatically, and provide the MATLAB code for use by others. The algorithm makes use of the wavelet decomposition of acquired signals, and employs different frequency regions to estimate the arrival of the extensional and the flexural mode. The algorithm automatically chooses a threshold value taking into account the noise content in the initial portion of each signal, and therefore requires no user input in general. Including the time-intensive process of reading data from and writing data to a computer data storage

drive, we show that our method can calculate the wave mode arrivals of signal at a rate of 1000 signals in every ≈ 40 s.

3. In practical applications of composite laminates, the loading scheme is more likely to be cyclic, varying between certain lower and upper limit, than increasing monotonically in nature. Moreover, the layup of plies used in increasingly diverse engineering applications is likely to be different from a simple cross-ply orientation. In Chapter 5, we investigate the deterioration of composite specimens of various different ply-layups under slow speed cyclic loading. We show that the ratio of certain energy components, between signals acquired by two piezoelectric sensors due to the same acoustic wave traveling to both sensors, can be used as a marker to indicate a fundamental change in material behavior that indicates future specimen failure.

This calculated peak energy ratio parameter shows similar easily observable changes in value for specimens of all tested ply-layups, and therefore should be adaptable for deployment in the field for composites with diverse ply sequences. Moreover, the observed fundamental change in property is shown to occur when an appreciable portion of service life remains in the specimen. For example, it would be an impractical marker that only indicates future failure with 5% of service life remaining, since a practical maintenance schedule cannot be planned against such a marker. We show that our calculated parameter undergoes observable changes with at least $\approx 20\%$ to 30% service life remaining, which makes this practically usable for planning maintenance or replacement schedules.

6.2 Future research directions

There are many avenues for future research to be conducted that would complement and extend the contributions of this dissertation. A few such directions are as follows:

- Investigate specimens with more complex shape and geometry, for example involving T-section or I-sections, where the fibers and matrix materials are arranged very differently than in usual laminates.
- 2. Subject specimens to cyclic loads at a higher loading frequency and moderate loading limits using hydraulic testing machines. This experimental setup will allow:
 - specimens to be run for much longer, and larger number of cycles, until failure.
 - experiments to be performed on much larger number of specimens. For such experiments, investigate the signals acquired from naturally occurring Acoustic Emission events for detection of critical damage.

Chapter 7

Bibliography

- [web, a] Acoustic Technology Group (ATG), piezoelectric sensors by Score-Atlanta. http: //www.atgndt.com/ae-sensors/sensors-score-atlanta/. Accessed: 27 July 2017.
- [web, b] Catalog of greases and lubricants, by Molykote from Dow Corning. http://www. dowcorning.com/content/publishedlit/80-3256.pdf. Accessed: 27 July 2017.
- [web, c] Demonstration of lamb wave symmetric and anti-symmetric modes. http://www. me.sc.edu/Research/lamss/research/Waves/sld004.htm. Accessed: 27 July 2017.
- [web, d] Dow Corning high-vacuum grease. http://www.dowcorning.com/applications/ search/products/details.aspx?prod=01018817&type=PROD&dsctry=USA. Accessed: 27 July 2017.
- [web, e] MathWorks file exchange repository submission. https://www.mathworks.com/ matlabcentral/fileexchange/63401. Accessed: 27 July 2017.
- [web, f] MATLAB wavelet toolbox, by MathWorks. https://www.mathworks.com/ products/wavelet.html. Accessed: 27 July 2017.

- [web,g] MTS universal testing machines. http://www.mts.com/en/products/ producttype/test-systems/load-frames-uniaxial/universal/electromechanical/ index.htm. Accessed: 27 July 2017.
- [web, h] Public repository at bitbucket.org. https://bitbucket.org/arnabocean/ wavemodearrivals. Accessed: 27 July 2017.
- [web, i] Wavelab850, a collection of MATLAB scripts for wavelet analysis. http:// statweb.stanford.edu/~wavelab/. Accessed: 27 July 2017.
- [Gle, 1985] (1985). Acoustic emission modulus determination and source location in unidirectional fibre reinforced polymer composites, Royal Naval Engineering Coll, Manadon, Engl.
- [Gho, 2002] (2002). Wave propagation sensing for damage detection in plates, volume 4693, Dept. of Mech. & Aerosp. Eng., Arizona State Univ., Tempe, AZ, USA. SPIE-Int. Soc. Opt. Eng.
- [Achenbach, 1973] Achenbach, J. (1973). *Wave propagation in elastic solids*. North-Holland Publishing Company, Amsterdam.
- [Aggelis et al., 2012a] Aggelis, D., Barkoula, N.-M., Matikas, T., and Paipetis, A. (2012a). Acoustic structural health monitoring of composite materials: Damage identification and evaluation in cross ply laminates using acoustic emission and ultrasonics. *Composites Science and Technology*, 72(10):1127–1133.
- [Aggelis et al., 2012b] Aggelis, D., Shiotani, T., Papacharalampopoulos, A., and Polyzos, D. (2012b). The influence of propagation path on elastic waves as measured by acoustic emission parameters. *Structural health monitoring*, 11(3):359–366.

- [Aggelis et al., 2010] Aggelis, D. G., Barkoula, N. M., Matikas, T. E., and Paipetis, A. S. (2010). Acoustic emission monitoring of degradation of cross ply laminates. *The Journal* of the Acoustical Society of America, 127(6):EL246–EL251.
- [Alleyne and Cawley, 1992] Alleyne, D. and Cawley, P. (1992). The interaction of Lamb waves with defects. *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control.*, 39(3):381–397.
- [Avanesians and Momayez, 2015] Avanesians, P. and Momayez, M. (2015). Wave separation: Application for arrival time detection in ultrasonic signals. *Ultrasonics*, 55:15 – 25.
- [Baxter et al., 2007] Baxter, M. G., Pullin, R., Holford, K. M., and Evans, S. L. (2007). Delta T source location for acoustic emission. *Mechanical Systems and Signal Processing*, 21(3):1512–1520.
- [Bhat et al., 1994] Bhat, M. R., Majeed, M. A., and Murthy, C. R. L. (1994). Characterization of fatigue damage in unidirectional GFRP composites through acoustic emission signal analysis. *NDT & E International*, 27(1):27–32.
- [Boczar and Lorenc, 2004] Boczar, T. and Lorenc, M. (2004). Determining the repeatability of acoustic emission generated by the Hsu-Nielsen calibrating source. *Molecular and quantum Acoustics*, 25(177-191):46.
- [Breckenridge et al., 1975] Breckenridge, F. R., Tschiegg, C. E., and Greenspan, M. (1975). Acoustic emission: some applications of Lamb's problem. *The Journal of the Acoustical Society of America*, 57(3):626–631.

- [Bussiba et al., 2008] Bussiba, A., Kupiec, M., Ifergane, S., Piat, R., and BÉĘhlke, T. (2008). Damage evolution and fracture events sequence in various composites by acoustic emission technique. *Composites Science and Technology*, 68(5):1144–1155.
- [Büssow, 2007] Büssow, R. (2007). An algorithm for the continuous morlet wavelet transform. *Mechanical Systems and Signal Processing*, 21(8):2970 – 2979.
- [Carpinteri, 2012] Carpinteri, A. (2012). *Handbook of fatigue crack propagation in metallic structures*. Newnes.
- [Chang et al., 2010] Chang, Y.-j., Zhang, K.-S., Hu, G.-j., and Jiao, G.-q. (2010). Characterization of tensile damage for 3D-C/SiC composites by acoustic emission. *Advanced Materials Research*, 97-101:834–837.
- [Chen et al., 2011] Chen, X., Li, J., Zhang, G., and Shi, Y. (2011). PZT nanoactive fiber composites for acoustic emission detection. *Advanced Materials Adv. Mater.*, 23(34):3965– 3969.
- [Ciampa and Meo, 2010] Ciampa, F. and Meo, M. (2010). A new algorithm for acoustic emission localization and flexural group velocity determination in anisotropic structures. *Composites Part A: Applied Science and Manufacturing*, 41(12):1777–1786.
- [Clough and Edwards, 2015] Clough, A. and Edwards, R. (2015). Characterisation of hidden defects using the near-field ultrasonic enhancement of lamb waves. *Ultrasonics*, 59:64–71.
- [Cohen and Kovacevic, 1996] Cohen, A. and Kovacevic, J. (1996). Wavelets: the mathematical background. *Proceedings of the IEEE Proceedings of the IEEE*, 84(4):514–522.
- [Curtis, 1974] Curtis, G. (1974). Acoustic emission 4: Spectral analysis of acoustic emission. *Non-Destructive Testing*, 7(2):82–91.

- [Deighton et al., 1981] Deighton, M. O., Gillespie, A. B., Pike, R. B., and Watkins, R. D. (1981). Mode conversion of Rayleigh and Lamb waves to compression waves at a metal-liquid interface. *Ultrasonics*, 19(6):249–258.
- [Doctor et al., 1996] Doctor, S. R., Nove, C. A., and Baaklini, G. Y., editors (1996). *Applications of advanced waveform-based AE techniques for testing composite materials*, volume 2944, Scottsdale, AZ, USA. SPIE.
- [Dong et al., 2011] Dong, W., Lin, Y., Zhongqing, S., and Ye, L. (2011). Quantitative identification of multiple damage in laminated composite beams using *A*₀ lamb mode. *Journal of Composite Materials*, 45(20):2061–2069.
- [Eaton et al., 2012] Eaton, M., Pullin, R., and Holford, K. (2012). Acoustic emission source location in composite materials using delta T mapping. *Composites Part A: Applied Science and Manufacturing*, 43(6):856–863.
- [Ernst and Dual, 2014] Ernst, R. and Dual, J. (2014). Acoustic emission localization in beams based on time reversed dispersion. *Ultrasonics*, 54(6):1522–1533.
- [Fleischmann et al., 1975] Fleischmann, P., Rouby, D., Lakestani, F., and Baboux, J. C. (1975). A spectrum analysis of acoustic emission. *Non-Destructive Testing*, 8(5):241–244.
- [Garg and Ishai, 1985] Garg, A. and Ishai, O. (1985). Characterization of damage initiation and propagation in graphite/epoxy laminates by acoustic emission. *Engineering Fracture Mechanics*, 22(4):595–608.
- [Gary and Hamstad, 1994] Gary, J. and Hamstad, M. (1994). On the far-field structure of waves generated by a pencil lead break on a thin plate. *Journal of Acoustic Emission*, 12(3/4):157–172.

- [Glennie and Summerscales, 1986] Glennie, A. M. G. and Summerscales, J. (1986). Acoustic emission source location in orthotropic materials. *British Journal of Non-Destructive Testing*, 28(1):17–22.
- [Gorman, 1991] Gorman, M. R. (1991). Plate wave acoustic emission. *Journal of the Acoustical Society of America*, 90(1):358–364.
- [Grabowska et al., 2008] Grabowska, J., Palacz, M., and Krawczuk, M. (2008). Damage identification by wavelet analysis. *Mechanical Systems and Signal Processing*, 22(7):1623–1635.
- [Gröchenig, 2001] Gröchenig, K. (2001). *Foundations of Time-Frequency Analysis*. Birkhäuser Boston.
- [Guo and Cawley, 1993] Guo, N. and Cawley, P. (1993). Lamb wave propagation in composite laminates and its relationship with acousto-ultrasonics. *NDT&E International*, 26(2):75–84.
- [Hamdi et al., 2013] Hamdi, S. E., Le, Duff, A., Simon, L., Plantier, G., Sourice, A., and Feuilloy, M. (2013). Acoustic emission pattern recognition approach based on hilberthuang transform for structural health monitoring in polymer-composite materials. *Applied Acoustics*, 74(5):746–757.
- [Hamstad, 1982] Hamstad, M. (1982). Acceptance testing of graphite /epoxy composite parts using an acoustic emission monitoring technique. *NDT International*, 15(6):307– 314.
- [He et al., 2011] He, P., Li, P., and Sun, H. (2011). Feature extraction of acoustic signals based on complex morlet wavelet. *Procedia Engineering*, 15:464–468.

- [Hou et al., 2004] Hou, J., Leonard, K. R., and Hinders, M. K. (2004). Automatic multimode lamb wave arrival time extraction for improved tomographic reconstruction. *Inverse Problems*, 20(6):1873.
- [Hsu and Breckenridge, 1981] Hsu, N. N. and Breckenridge, F. R. (1981). Characterization and calibration of acoustic emission sensors. *Materials Evaluation*, 39:60–68.
- [Janardhan and Balasubramaniam, 2014] Janardhan, P. M. and Balasubramaniam, K. (2014). Lamb-wave-based structural health monitoring technique for inaccessible regions in complex composite structures. *Structural Control and Health Monitoring*, 21(5):817–832.
- [Jeong, 2001] Jeong, H. (2001). Analysis of plate wave propagation in anisotropic laminates using a wavelet transform. *NDT & E International*, 34(3):185–190.
- [Jeong and Jang, 2000a] Jeong, H. and Jang, Y.-S. (2000a). Fracture source location in thin plates using the wavelet transform of dispersive waves. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control,* 47(3):612–619.
- [Jeong and Jang, 2000b] Jeong, H. and Jang, Y.-S. (2000b). Wavelet analysis of plate wave propagation in composite laminates. *Composite Structures*, 49(4):443–450.
- [Jiao et al., 2004] Jiao, J., He, C., Wu, B., Fei, R., and Wang, X. (2004). Application of wavelet transform on modal acoustic emission source location in thin plates with one sensor. *International Journal of Pressure Vessels and Piping*, 81(5):427–431.
- [Jingpin et al., 2008] Jingpin, J., Bin, W., and Cunfu, H. (2008). Acoustic emission source location methods using mode and frequency analysis. *Structural Control and Health Monitoring*, 15(4):642–651.

- [Kaiser, 1950] Kaiser, J. (1950). Results and Conclusions from Measurements of Sound in Metallic Materials under Tensile Stress. PhD thesis, Technische Hochshule Munich.
- [Kaphle et al., 2012] Kaphle, M., Tan, A. C. C., Thambiratnam, D. P., and Chan, T. H. T. (2012). Identification of acoustic emission wave modes for accurate source location in plate-like structures. *Structural Control and Health Monitoring*, 19(2):187–198.
- [Kessler et al., 2002] Kessler, S. S., Spearing, S. M., and Soutis, C. (2002). Damage detection in composite materials using Lamb wave methods. *Smart Materials and Structures*, 11(2):269–278.
- [Keulen et al., 2014] Keulen, C. J., Yildiz, M., and Suleman, A. (2014). Damage detection of composite plates by lamb wave ultrasonic tomography with a sparse hexagonal network using damage progression trends. *Shock & Vibration*, pages 1–8.
- [Kishimoto et al., 1995] Kishimoto, K., Inoue, H., Hamada, M., and Shibuya, T. (1995).
 Time frequency analysis of dispersive waves by means of wavelet transform. *Journal of Applied Mechanics Journal of Applied Mechanics J. Appl. Mech.*, 62(4):841–846.
- [La Saponara et al., 2011] La Saponara, V., Horsley, D. A., and Lestari, W. (2011). Structural health monitoring of glass/epoxy composite plates using PZT and PMN-PT transducers. *Journal of Engineering Materials and Technology Journal of Engineering Materials and Technology J. Eng. Mater. Technol.*, 133(1):011011–011018.
- [Lamb, 1917] Lamb, H. (1917). On waves in an elastic plate. Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character, 93(648):114–128.
- [Ledbetter and Kriz, 1982] Ledbetter, H. M. and Kriz, R. D. (1982). Elastic-wave surfaces in solids. *physica status solidi* (*b*), 114(2):475–480.

- [Lee and Staszewski, 2003a] Lee, B. C. and Staszewski, W. J. (2003a). Modelling of lamb waves for damage detection in metallic structures: Part I. wave propagation. *Smart materials and structures*, 12(5):804–814.
- [Lee and Staszewski, 2003b] Lee, B. C. and Staszewski, W. J. (2003b). Modelling of lamb waves for damage detection in metallic structures: Part II. wave interactions with damage. *Smart materials and structures*, 12(5):815–824.
- [Lee et al., 2011] Lee, J.-S., Park, G., Kim, C.-G., and Farrar, C. R. (2011). Use of relative baseline features of guided waves for in situ structural health monitoring. *Journal of Intelligent Material Systems and Structures*, 22(2):175–189.
- [Leone et al., 2012] Leone, C., Lopresto, V., Papa, I., and Caprino, G. (2012). Triangulation method as a valid tool to locate the damage in unidirectional CFRP laminates. *Composite Structures*, 94(8):2418–2423.
- [Lympertos and Dermatas, 2007] Lympertos, E. M. and Dermatas, E. S. (2007). Acoustic emission source location in dispersive media. *Signal Processing*, 87(12):3218–3225.
- [Mallat, 1989] Mallat, S. (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(7):674–693.
- [Mallat, 2008] Mallat, S. G. (2008). A Wavelet Tour of Signal Processing. Academic Press.
- [Nair and Cai, 2010] Nair, A. and Cai, C. (2010). Acoustic emission monitoring of bridges: Review and case studies. *Engineering Structures*, 32(6):1704 – 1714.
- [Nakken, 1999] Nakken, M. (1999). Wavelet analysis of rainfall-runoff variability isolating climatic from anthropogenic patterns. *Environmental Modelling & Software*, 14(4):283–295.

- [Nayfeh AH, 1989] Nayfeh AH, C. D. (1989). Free wave propagation in plates of general anisotropic media. *Journal of Applied Mechanics, Transactions ASME*, 56(4):881–886.
- [Ono and Huang, 1995] Ono, K. and Huang, Q. (1995). Dynamic characterization of composite fracture mechanics with pattern recognition of acoustic emission signals. *Advanced Structural Fiber Composites*, pages 551–558.
- [Oskouei, 2009] Oskouei, A. R. (2009). Wavelet-based acoustic emission characterization of damage mechanism in composite materials under mode I delamination at different interfaces. *Express Polymer Letters*, 3(12):804–813.
- [Pao et al., 1979] Pao, Y.-H., Gajewski, R. R., and Ceranoglu, A. N. (1979). Acoustic emission and transient waves in an elastic plate. *The Journal of the Acoustical Society of America*, 65(1):96–105.
- [Pearson, 1975] Pearson, S. (1975). Initiation of fatigue cracks in commercial aluminium alloys and the subsequent propagation of very short cracks. *Engineering Fracture Mechanics*, 7(2):235–247.
- [Peng et al., 2002] Peng, Z., Chu, F., and He, Y. (2002). Vibration signal analysis and feature extraction based on reassigned wavelet scalogram. *Journal of Sound and Vibration*, 253(5):1087–1100.
- [Perrier et al., 1995] Perrier, V., Philipovitch, T., and Basdevant, C. (1995). Wavelet spectra compared to fourier spectra. *Journal of Mathematical Physics Journal of Mathematical Physics J. Math. Phys.*, 36(3):1506–1519.
- [Plumbridge, 1972] Plumbridge, W. (1972). Fatigue-crack propagation in metallic and polymeric materials. *Journal of Materials Science*, 7(8):939–962.

- [Pomponi et al., 2015] Pomponi, E., Vinogradov, A., and Danyuk, A. (2015). Wavelet based approach to signal activity detection and phase picking: Application to acoustic emission. *Signal Processing*, 115:110 – 119.
- [Proakis and Manolakis, 2007] Proakis, J. G. and Manolakis, D. G. (2007). *Digital signal processing: principles, algorithms, and applications*. Pearson Prentice Hall.
- [Proctor et al., 1983] Proctor, T. M., Breckenridge, F. R., and Pao, Y. H. (1983). Transient waves in an elastic plate: Theory and experiment compared. *The Journal of the Acoustical Society of America*, 74(6):1905–1907.
- [Prosser and Gorman, 1994] Prosser, W. H. and Gorman, M. R. (1994). Plate mode velocities in graphite/epoxy plates. *The Journal of the Acoustical Society of America*, 96(2):902– 907.
- [Prosser et al., 1999] Prosser, W. H., Hamstad, M. A., Gary, J., and O'Gallagher, A. (1999). Reflections of AE waves in finite plates: Finite element modeling and experimental measurements. *Journal of Acoustic Emission*, 17:37–47.
- [Qi, 2000] Qi, G. (2000). Wavelet-based AE characterization of composite materials. NDT
 & E International, 33(3):133–144.
- [Rao et al., 2007] Rao, Y. J., Liao, Y. B., and Peng, G. D., editors (2007). Study on location of analog source of optical fiber acoustic emission - art. no. 68301M, Beijing. Spie-Int Soc Optical Engineering.
- [Reifsnider et al., 2000] Reifsnider, K., Case, S., and Duthoit, J. (2000). The mechanics of composite strength evolution. *Composites Science and Technology*, 60(12-13):2539–2546.
- [Reifsnider and Jamison, 1982] Reifsnider, K. and Jamison, R. (1982). Fracture of fatigueloaded composite laminates. *International Journal of Fatigue*, 4(4):187–197.

- [Reifsnider and Talug, 1980] Reifsnider, K. and Talug, A. (1980). Analysis of fatigue damage in composite laminates. *International Journal of Fatigue*, 2(1):3–11.
- [Rhee et al., 2007] Rhee, S.-H., Lee, J.-K., and Lee, J.-J. (2007). The group velocity variation of lamb wave in fiber reinforced composite plate. *Ultrasonics*, 47(1-4):55–63.
- [Sause et al., 2013] Sause, M. G., Hamstad, M. A., and Horn, S. (2013). Finite element modeling of lamb wave propagation in anisotropic hybrid materials. *Composites Part B: Engineering*, 53:249–257.
- [Sause, 2011] Sause, M. G. R. (2011). Investigation of pencil-lead breaks as acoustic emission sources. *Journal of Acoustic Emission*, 29:184–196.
- [Schmitt et al., 2013] Schmitt, M., Olfert, S., Rautenberg, J., Lindner, G., Henning, B., and Reindl, L. (2013). Multi reflection of lamb wave emission in an acoustic waveguide sensor. *Sensors (Basel)*, 13(3):2777–2785.
- [Scholey et al., 2010] Scholey, J. J., Wilcox, P. D., Wisnom, M. R., and Friswell, M. I. (2010). Quantitative experimental measurements of matrix cracking and delamination using acoustic emission. *Composites Part A: Applied Science and Manufacturing*, 41(5):612–623.
- [Schubert et al., 2014] Schubert, K. J., Brauner, C., and Herrmann, A. S. (2014). Nondamage-related influences on lamb wave-based structural health monitoring of carbon fiber-reinforced plastic structures. *Structural Health Monitoring*, 13(2):158–176.
- [Scruby, 1987] Scruby, C. B. (1987). An introduction to acoustic emission. *Journal of Physics E (Scientific Instruments)*, 20(8):946–953.
- [Serrano and Fabio, 1996] Serrano, E. P. and Fabio, M. A. (1996). Application of the wavelet transform to acoustic emission signals processing. *Signal Processing, IEEE Transactions on,* 44(5):1270–1275.

- [Shyu and Sun, 2002] Shyu, H.-C. and Sun, Y.-S. (2002). Construction of a morlet wavelet power spectrum. *Multidimensional Systems and Signal Processing*, 13(1):101–111.
- [Smith, 2003] Smith, R. C., editor (2003). *Lamb wave interaction with structural defects: modeling and simulations*, volume 5049(1), San Diego, CA, USA. SPIE.
- [Solie and Auld, 1973] Solie, L. P. and Auld, B. A. (1973). Elastic waves in free anisotropic plates. *The Journal of the Acoustical Society of America*, 54(1):50–65.
- [Stinchcomb, 1986] Stinchcomb, W. (1986). Nondestructive evaluation of damage accumulation processes in composite laminates. *Composites Science and Technology*, 25(2):103– 118.
- [Stoica et al., 2005] Stoica, P., Moses, R. L., et al. (2005). *Spectral analysis of signals*, volume452. Pearson Prentice Hall Upper Saddle River, NJ.
- [Subramanian et al., 1995] Subramanian, S., Reifsnider, K., and Stinchcomb, W. (1995). A cumulative damage model to predict the fatigue life of composite laminates including the effect of a fibre-matrix interphase. *International Journal of Fatigue*, 17(5):343–351.
- [Surgeon and Wevers, 1999] Surgeon, M. and Wevers, M. (1999). Modal analysis of acoustic emission signals from CFRP laminates. *NDT & E International*, 32(6):311–322.
- [Suzuki et al., 1996] Suzuki, H., Kinjo, T., Hayashi, Y., Takemoto, M., and Ono, K. (1996). Wavelet transform of acoustic emission signals. *Journal of Acoustic Emission*, 14(2):69–84.
- [Tan et al., 1995] Tan, K., Guo, N., Wong, B., and Tui, C. (1995). Comparison of lamb waves and pulse echo in detection of near-surface defects in laminate plates. *NDT & E International*, 28(4):215–223.

- [Tang et al., 2011] Tang, H.-Y., Winkelmann, C., Lestari, W., and La, Saponara, V. (2011). Composite structural health monitoring through use of embedded PZT sensors. *Journal* of Intelligent Material Systems and Structures, 22(8):739–755.
- [Toyama et al., 2001] Toyama, N., Koo, J. H., Oishi, R., Enoki, M., and Kishi, T. (2001). Two-dimensional AE source location with two sensors in thin CFRP plates. *Journal of Materials Science Letters*, 20(19):1823–1825.
- [Toyama et al., 2003a] Toyama, N., Noda, J., and Okabe, T. (2003a). Quantitative damage detection in cross-ply laminates using lamb wave method. *Composites Science and Technology*, 63(10):1473–1479.
- [Toyama et al., 2003b] Toyama, N., Okabe, T., and Takeda, N. (2003b). Lamb wave evaluation and localization of transverse cracks in cross-ply laminates. *Journal of Materials Science*, 38(8):1765–1771.
- [Toyama et al., 2002] Toyama, N., Okabe, T., Takeda, N., and Kishi, T. (2002). Effect of transverse cracks on lamb wave velocity in CFRP cross-ply laminates. *Journal of Materials Science Letters*, 21(4):271–273.
- [Valdes and Soutis, 2002] Valdes, S. H. D. and Soutis, C. (2002). Real-time nondestructive evaluation of fiber composite laminates using low-frequency lamb waves. *The Journal of the Acoustical Society of America*, 111(5):2026–2033.
- [Vetterli and Herley, 1992] Vetterli, M. and Herley, C. (1992). Wavelets and filter banks: theory and design. *IEEE Transactions on Signal Processing*, 40(9):2207–2232.
- [Viktorov, 1970] Viktorov, I. A. (1970). Rayleigh and Lamb Waves. Plenum Press.

- [Wang and Yuan, 2007] Wang, L. and Yuan, F. G. (2007). Group velocity and characteristic wave curves of lamb waves in composites: Modeling and experiments. *Composites Science and Technology*, 67(7-8):1370–1384.
- [Wink and Roerdink, 2004] Wink, A. and Roerdink, J. (2004). Denoising functional MR images: a comparison of wavelet denoising and gaussian smoothing. *IEEE Transactions on Medical Imaging*, 23(3):374–387.
- [Yoji et al., 2010] Yoji, O., Fujibayashi, K., Shimazaki, M., Soejima, H., and Ogisu, T. (2010).
 Delamination detection in composite laminates using dispersion change based on mode conversion of lamb waves. *Smart Materials and Structures*, 19(11):115013.
- [Ziola and Gorman, 1991] Ziola, S. M. and Gorman, M. R. (1991). Source location in thin plates using cross-correlation. *The Journal of the Acoustical Society of America*, 90(5):2551–2556.