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Neural Network Detection of Fatigue Crack Growth in Riveted Joints Using Acoustic Emission

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NEURAL NETWORK DETECTION OF FATIGUE CRACK GROWTH
IN RIVETED JOINTS USING ACOUSTIC EMISSION

by Adriano F. de Almeida

A Thesis Submitted to the Office of Graduate Programs in
Partial Fulfillment of the Requirements for the Degree of
Master of Science in Aerospace Engineering

Embry-Riddle Aeronautical University
Daytona Beach, Florida
May 1994
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This thesis was prepared under the direction of the candidate's thesis committee chairman, Dr. Eric v. K. Hill, Department of Aerospace Engineering, and has been approved by the members of his thesis committee. It was submitted to the Office of Graduate Programs and was accepted in partial fulfillment of the requirements for the degree of Master of Science in Aerospace Engineering.

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Finally, I would like to thank Dr. John Carlyle for his valuable advice and the willingness to share his knowledge of acoustic emission and data acquisition. His remarkable accomplishments and easy-going character have been an inspiration.
The purpose of this research was to demonstrate the capability of neural networks to discriminate between individual acoustic emission (AE) signals originating from crack growth and rivet rubbing (fretting) in aluminum lap joints. AE waveforms were recorded during tensile fatigue cycling of six notched and riveted 7075-T6 specimens using a broadband piezoelectric transducer and a computer interfaced oscilloscope. The source of 1,311 signals was identified based on triggering logic, amplitude relationships, and time of arrival data collected from the broadband transducer and three additional 300 Hz resonant transducers bonded to the specimens. The power spectrum of each waveform was calculated and normalized to correct for variable specimen geometry and wave propagation effects. In order to determine the variation between individual signals of the same class, the normalized spectra were clustered onto a two-dimensional feature space using a Kohonen self organizing map (SOM). Then 132 crack growth and 137 rivet rubbing spectra were used to train a back-propagation neural network to provide automatic pattern classification. Although there was some overlap between the clusters mapped in the Kohonen feature space, the trained back-propagation neural network was able to classify the remaining 463 crack growth signals with a 94% accuracy and the 367 rivet rubbing signals with a 99% accuracy.
# TABLE OF CONTENTS

## LIST OF TABLES

| v | vii |

## LIST OF FIGURES

| vi | viii |

## CHAPTER 1 INTRODUCTION

<table>
<thead>
<tr>
<th>1</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem Identification</td>
<td>1</td>
</tr>
<tr>
<td>Previous Research</td>
<td>3</td>
</tr>
</tbody>
</table>

## CHAPTER 2 FUNDAMENTALS OF ACOUSTIC EMISSION

<table>
<thead>
<tr>
<th>2</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acoustic Emission Sources</td>
<td>7</td>
</tr>
<tr>
<td>Wave Propagation</td>
<td>8</td>
</tr>
<tr>
<td>Sensors and Pre-Amps</td>
<td>11</td>
</tr>
</tbody>
</table>

## CHAPTER 3 DATA ACQUISITION

<table>
<thead>
<tr>
<th>3</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental Setup</td>
<td>15</td>
</tr>
<tr>
<td>Instrumentation</td>
<td>25</td>
</tr>
<tr>
<td>System Calibration</td>
<td>28</td>
</tr>
</tbody>
</table>

## CHAPTER 4 SIGNAL PROCESSING

<table>
<thead>
<tr>
<th>4</th>
<th>33</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Analysis</td>
<td>33</td>
</tr>
<tr>
<td>Data Normalization and Reduction</td>
<td>37</td>
</tr>
</tbody>
</table>

## CHAPTER 5 NEURAL NETWORK CLASSIFICATION

<table>
<thead>
<tr>
<th>5</th>
<th>39</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Overview</td>
<td>39</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 5 1 Learning Schedule Used for this Application 48

Table 6 1 Summary of Data Acquisition Results 51

Table 6 2 Training and Testing Files Used for Neural Network Implementation 55

Table 6 3 Final Results for Neural Network Classification 56
LIST OF FIGURES

Figure 1 1  Schematic of Concept Used to Classify Individual AE Signals 2

Figure 2 1  Dispersion Curves for the First Two Lamb Wave Modes in 0.06 Inch Thick Aluminum Sheet 9

Figure 2 2  Response Curve for a 300 kHz Resonant Sensor as Supplied by the Manufacturer (PAC) 12

Figure 2 3  Response Curve for a 0.1-1.0 MHz Broad-Band Sensor as Supplied by the Manufacturer (PAC) 12

Figure 2 4  Comparison Between the Output from a Resonant and a Broad-Band Sensor 13

Figure 3 1  Specimen Configurations and Sensor Placement 15

Figure 3 2  Detailed Drawing of Joint Configuration 17

Figure 3 3  Riveted Specimen Fixed to the MTS Grips 18

Figure 3 4  Photograph of Crack Taken with the Photo-Microscope (x 75 Amplification) 19

Figure 3 5  Load Cycle Indicating Region in which Data was Recorded 20

Figure 3 6  Hits Versus Load Plot for Tensile Specimen Without Rivets 21

Figure 3 7  Hits Versus Load for a Riveted Specimen Before Crack Initiation 22

Figure 3 8  Hits Versus Load for a Riveted Specimen After Crack Initiation 22

Figure 3 9  Location Data Produced by Cracked Specimen 23

Figure 3 10  Schematic of the Instrumentation Setup 25

Figure 3 11  Laboratory Setup 26

Figure 3 12  Schematic of the Voltage Gate Circuit 28

Figure 3 13  Sample Calibration Set from Pencil-Lead Breaks 31
CHAPTER 1
INTRODUCTION

The following chapter describes the problem addressed by this thesis. An historical overview of previous research on acoustic emission monitoring of aircraft structures is also provided in order to emphasize the significance of this work and the potential for further developments along the same line.

1.1 Problem Identification

Acoustic emission (AE) is the name given to the elastic waves which are emitted by materials as they react to applied stresses. The phenomenon was first studied in Germany during the late 1940s and has since evolved into a powerful technique for evaluating the integrity of structures and studying material properties. One of the most important applications of acoustic emission is its ability to detect growing flaws in structures while they are still in service. Other nondestructive testing methods such as ultrasonic, eddy-current, and radiography, require direct energy input in order to detect the presence of flaws. With acoustic emission, the energy is released by the flaw itself as the structure is loaded. This basic difference is what makes acoustic emission such a powerful technique. With the use of piezoelectric transducers, amplifiers, and signal processing devices, acoustic emission offers the capability of detecting active flaws long before any other nondestructive testing method.

Although AE technology has advanced significantly in the past twenty years, there is still one fundamental problem which hinders its widespread acceptance as a reliable method of nondestructive testing. When AE is applied to fatigue monitoring of metal joints, excessive noise resulting from fastener rubbing makes real time detection of crack
growth difficult and unreliable. Commercially available systems are not capable of automatically discriminating between signals from crack growth and fretting, especially when they are emitted from the same location. In most cases, positive classification of individual signals requires experienced personnel and post test data analysis, which tends to increase the cost of the technology. In order to enable the widespread use of acoustic emission for monitoring complex structures, improved signal processing methods must be devised to provide automatic discrimination between relevant signals and structural noise.

In the following research, neural network signal pattern recognition has been applied to address this problem. As shown in Figure 1.1, a neural network was trained to classify individual AE signals based on the overall shape of the frequency spectra. Gorman and Sejnowski [2] applied a similar concept to identify submarine sonar targets and found that a back-propagation neural network performed significantly better than a feature based nearest neighbor classifier.

![Figure 1.1. Schematic of Concept Used to Classify Individual AE Signals.](image-url)
1.2 Previous Research

The suitability of acoustic emission for monitoring aircraft structures has been established in the past. It is common knowledge, however, that the problem is difficult and challenging due to complicated geometries, high noise levels, and complex loadings. AE waveforms can undergo multiple mode conversions, resulting in complex signals at the sensor, thereby adding to the difficulty of source location and classification. Further complication is associated with the fact that flaws usually initiate at fastener holes, which tend to emit fretting noises while the flaw grows. Since the early 1970s, several studies have investigated the application of AE to monitoring aircraft structures. The remainder of this chapter gives an overview of these efforts.

In 1970, Nakamura [3] from General Dynamics described a method for monitoring complex structures which relied on slave sensors and logic gates to provide spatial filtering. The disadvantage of his approach was that flaw growth AE could be lost if they occurred while the logic gates were closed by signals from structural noise. Despite this drawback, spatial filtering is still employed in AE testing today.

In 1976, Mizell and Lundy [4] from the Oklahoma City Air Logistics Center published a paper describing the development of an acoustic emission in-flight crack detection system to monitor lower wing skin panels of the KC-135 aircraft. Although the system could detect unstable crack extensions (greater than 1 inch) in the 7075-T6 aluminum panels, it was not completely immune to structural noise and electromagnetic interference. In 1978, Parish redesigned the system and eliminated the problem of false triggering due to background noise [5]. The improved system was more reliable, but it was limited since it could not detect small crack extensions.

During the mid 1970s, at the Lockheed-Georgia Company, Bailey and Pless [6] detected microscopic crack extensions during fatigue tests of aircraft components. Their ambitious efforts pointed to the possibility of developing a system capable of detecting
stable crack growth in flight. However, they encountered problems with background noise and signal processing which needed to be overcome before reliable in-flight crack detection could be provided.

During the 1980s, McBride and Maclachlan [7,8] from the Royal Military College of Canada published valuable research on in-flight monitoring of stable crack growth in CF-100 and CC-130 aircraft. To show that the presence of a crack is detectable during flight, their approach focused on monitoring a specific component with a known crack source. McBride and Maclachlan are also known for their studies of AE from fracture mechanisms in aluminum alloys [9,10]. They originally proposed that the major source of AE during crack growth in 7075 aluminum was fracture of Mg-Si inclusions by the advancing crack tip. Recent work by Heiple et al. [11] has challenged their theory, claiming that crack growth itself is the primary source of AE and that the amplitude of emissions from fracture of individual inclusion particles is too low to account for the signals generally observed.

Also during the early 1980s, scientists in Australia, Canada, England, and the United States participated in an effort to characterize acoustic emission frequency spectra from crack growth. They employed a method proposed by Carlyle to correct AE spectra for the variable effects of specimen geometry, sensor placement, and instrumentation characteristics [12]. The encouraging results obtained led to further applications of the concept. At Rockwell International, Graham and Elsley [13] used frequency based features to obtain better than 90% classification accuracy between crack growth, crack face rubbing, and fretting in aluminum specimens. Four years later, at the Australian Aeronautical Research Laboratories, Scala and Coyle [14] detected fatigue cracks in the main spar of a Mirage aircraft using semi-adaptive pattern recognition. Although their method was effective, they concluded that it was not well suited for real-time, in-flight applications due to the complex computing requirements.
Efforts aimed at characterizing AE through adaptive, knowledge based techniques have been limited. The advantage of this approach is that complex and highly un reproduceable signals can be classified by incorporating the maximum amount of knowledge available about the source. Research in this area was published in 1984 by Robert Hay [15], who combined time-domain pulse information, signal frequency distribution, and frequency shifts of the cumulative power spectrum to provide classification of AE sources from deformation mechanisms in aluminum alloys. Although Hay's approach involved the extraction of up to thirty features from a single waveform, it is believed that only a few well-chosen features are normally required to obtain accurate recognition. In fact, it was the complexity of his approach which led to its limited application. As faster computers and improved pattern recognition methods become available, complex problems can be solved more efficiently.

In the 1990s, AE technology continues to gain ground in the aviation industry. Dr John Carlyle of Physical Acoustics Corporation has worked on various projects to detect flaws in aircraft structures [16-18]. However, he does not make use of neural computing techniques for classifying individual AE sources based on their frequency content. The recent development of advanced neural networks has provided the means for automatic pattern classification of AE spectra with incredible speeds and very good accuracy.

Automatic modeling of AE using neural networks is being pursued by Sachse and Grabec [19]. By applying neural computing techniques to classify signals generated by breaking different sizes of pencil leads, they showed that neural networks can provide precise pattern recognition between similar sources. In 1992, Yuki and Homma from the University of Electro-Communications in Tokyo also demonstrated the capability of neural networks for classification of simulated sources [20].

Although previous work provides an indication of the potential of neural networks for improving AE technology, more research is still required. When AE is emitted by real structures undergoing dynamic loading, the recorded signals tend to be more complex and
more difficult to classify than simulated sources emitted from a known origin in simple specimens. In order to fully understand the applicability and limitations of neural network AE pattern classification, it is desirable to consider more realistic scenarios, which require more complicated analyses.
CHAPTER 2
FUNDAMENTALS OF ACOUSTIC EMISSION

The following chapter covers the principals of acoustic emission (AE) which relate to signals recorded for this research. Characterization of AE signals relies on an understanding of the mechanisms which caused them, the way in which they propagate, and the means by which they are transformed from stress waves to electrical signals.

2.1 Acoustic Emission Sources

When AE techniques are applied to monitoring of complex structural joints, typically there are several sources which can be detected as the joint is subjected to stress. These sources are characterized by a rapid release of internal energy, resulting in the generation of a propagating acoustic wave. Some examples of AE sources which may exist during fatigue cycling of aluminum alloys include crack initiation and advance, dislocation motion in the plastic zone, fracture of inclusion particles, and fretting between rubbing parts. In 1992 Heiple et al. postulated that the most plausible source of AE during fatigue cracking of 7075 aluminum is crack advance itself [11]. For the riveted specimens tested in this research, fretting, caused by sudden abrasive motion between contacting surfaces, was the source of most signals encountered.

Since the orientation of grains, distribution of inclusion particles, local stress field at the crack tip, and relative position of fretting surfaces is inherently random, the investigator has no control over the waves released by each source. These factors make AE source characterization a challenging task, since individual waves emitted by the same type of source can vary tremendously in energy, amplitude, frequency, and duration. This explains why the primary approach to AE data analysis has been statistical in nature.
Although a statistical approach is effective in some cases, it relies on detection of a large number of AE from a given source. This requirement may be incompatible with in-flight monitoring of aircraft structures, where the detection of a few crack events can represent an emergency.

2.2 Wave Propagation

Classical wave theory has been used to describe the amplitude, frequency, wavelength and speed of propagation of AE bursts as a combination of sine waves. Since any complex function can be represented by the sum of sinusoidal components through Fourier analysis, realistic waveforms can be modeled with this approach. Solution to the wave equation leads to the determination of different wave modes, depending on the boundary conditions imposed. The solution for an infinite, isentropic, and homogeneous medium results in the longitudinal and shear modes, with each forming a complete and independent set of eigenfunctions. In aluminum, the average longitudinal wave speed is $2.5 \times 10^5$ in/sec (6,320 m/s) and the average shear wave speed is $1.2 \times 10^4$ in/sec (3,080 m/s). Though common in other areas of acoustics, these wave modes are seldom encountered in their pure forms during AE testing.

For an infinite medium with stress-free surfaces, the Rayleigh wave and Lamb wave modes are found. Since most AE applications rely on wave propagation along a free surface, identification of these modes is very useful for practical AE testing. The Rayleigh wave mode represents the solution to the wave equation for a semi-infinite medium, so it can be used to model surface propagation of waves in thick members. Lamb waves apply to plates and are represented by an infinite number of symmetric and anti-symmetric modes for which the speeds of propagation vary with frequency. For most AE applications, the lower order Lamb modes are most significant, since the other modes exist only at relatively high frequencies. Lamb waves have been described as a series of
reflecting and mode converting longitudinal and shear waves which establish coherent propagating modes [21].

For thin plates, or at low frequencies, velocity variations between the different Lamb wave modes is significant. This phenomenon is illustrated in Figure 2.1, which shows the velocity dispersion curves for the first two Lamb wave modes as a function of frequency in a 0.06 inch thick aluminum sheet [22]. Velocity dispersion tends to make a short pulse extend in duration and lose amplitude as it propagates to large distances. Since several modes can exist simultaneously, the velocity of Lamb waves is usually represented by a group velocity. The group velocity approaches the Rayleigh wave velocity as the product of plate thickness and frequency increases [23].

![Figure 2.1. Dispersion Curves for the First Two Lamb Wave Modes in 0.06 Inch Thick Aluminum Sheet [22]](image-url)
Although velocity dispersion is an important factor when testing large structures, it is not as significant in small tensile specimens because of the short propagation distances. Another consideration, which is more important, is the effect of wavefront curvature. Since AE point sources generate expanding spherical (or circular) waves, significant curvature of the wave front exists in the near-field. Close to the source, the classical wave approach is not applicable since it does not account for wavefront curvature. Near-field effects should not be overlooked, especially when considering the early part of AE waveforms to extract information about the source pulse [21].

A property of wave propagation important in small specimens is wave reflection. When a wave reaches the boundary between two materials, the amount of energy which is reflected back or transmitted depends on the angle of incidence of the wave and the acoustic impedance of both materials. If the acoustic impedance is very different, such as that between aluminum and air, the majority of the wave is reflected, but if it is fairly equal, most of the wave is transmitted. As a result of alternate wave paths and multiple reflections, the frequency content of signals from small specimens tends to be very different from those in large plates.

Another important effect considered during AE testing is attenuation, which is a measure of the loss of amplitude of a wave as it propagates. Attenuation is caused primarily by velocity dispersion, wave coupling into adjacent media, internal friction and geometric spreading of the wave. Attenuation levels in a given structure are highly dependent on the material, its geometry, and the frequency range in question. In general, higher frequencies are attenuated more, but certain structural configurations, such as thin plates, may favor a higher frequency. It is good practice to perform attenuation measurements prior to beginning a test since it will help determine sensor spacing and threshold levels. In small metal specimens, attenuation is not a major factor, although the effect can be observed. The presence of a sensor causes attenuation since part of the wave will couple into the sensor face. Moreover, the change in geometry and air gap associated
with a joint will generally attenuate higher frequency components due to internal friction and reflections.

2.3 Sensors and Pre-Amps

Since the time response and frequency content of propagating waves can vary significantly for different applications, a wide selection of specialized AE sensors are commercially available. The proper choice of a sensor requires an understanding of not only wave propagation, but also the nature of existing background noise. When performing experiments in the presence of extraneous mechanical or hydraulic noise, for example, it may be required to use high frequency resonant sensors to enable detection of low amplitude crack growth emissions.

AE sensors can be classified as resonant or broad-band, depending on their response. Resonant sensors are generally used in combination with band-pass filters so that the output will preserve primarily the resonant frequency. The response curve for a typical 300 kHz resonant sensor is shown in Figure 2.2. Notice that although this sensor responds to a wide range of frequencies, the peak sensitivity is at 350 kHz. By filtering the output between 200 and 400 kHz improved sensitivity can be obtained.

When performing frequency spectrum analysis, it is desirable to retain the maximum amount of information over a wide range of frequencies. This requirement calls for sensors with relatively flat response curves. Figure 2.3 shows the response curve for a broad-band sensor. Although it is not very flat, it provides good sensitivity between 0.20 and 1.0 MHz. Compared with the filtered outputs from resonant sensors, unfiltered AE signals from broad-band sensors are noisier and more complicated. The general difference between AE waveforms collected by resonant and broad-band sensors is illustrated in Figure 2.4. Since resonant sensors detect only the energy over a narrow frequency band, they are not suitable for AE frequency analysis.
Figure 2.2. Response Curve for a 300 kHz Resonant Sensor as Supplied by the Manufacturer (PAC)

Figure 2.3. Response Curve for a 0.1-1.0 MHz Broad-Band Sensor as Supplied by the Manufacturer (PAC)
The standard unit used for calibrating the response of an AE sensor is decibels (dB) referenced to 1 volt/microbar (1 bar = 14.5 psi = 0.986 atm). This quantity relates the output signal to a known pressure level at the sensor face. Although the manufacturer's calibration data is a useful reference, it does not provide a complete picture, since the response also depends on how the output is amplified and how the sensor face is coupled to the surface of the test article.

Because the actual charge produced by the piezoelectric element in AE sensors is very small, amplification of the signal is an important factor for maximizing sensitivity. In order to optimize the sensor's response, signal amplification should occur as close to the sensor as possible. This is because the voltage output of the element is inversely proportional to the total capacitance of the sensor, cable and pre-amp. If the wrong cable is used to connect the sensor to the pre-amp, the sensitivity can be reduced dramatically.
Once the signal is amplified, however, it can be transferred through long co-axial cables without much loss. Signal amplification can be used to increase sensitivity only to a certain extent, depending on the dynamic range of the system. Dynamic range is a measure of how much voltage output an amplifier can provide before the input noise voltage causes distortion of the output signal. Since pre-amp noise has a significant effect on the frequency response of recorded signals, large dynamic ranges and signal-to-noise ratios are desirable when performing spectral analysis.

Another important factor influencing sensor response is the method by which the sensor is coupled to a surface. Various types of couplants can be used, but changing couplants can produce significant differences in the stimulation of the sensor face, thus changing the response. Throughout this research, five-minute epoxy was used. It provided a bond for the sensor in addition to a transmission medium for the acoustic waves. Couplants such as oil or grease result in better sensitivity than epoxy, but they tend to be messy and require additional fixtures. One of the disadvantages of rigid bonds is that they can fatigue or fracture due to differential displacement between the bonded surfaces. This, however, was not a problem here.
CHAPTER 3
DATA ACQUISITION

This chapter discusses the experimental method employed to obtain the acoustic emission data necessary for neural network development. A description of the instrumentation is provided together with procedures used to produce reference signals for data normalization.

3.1 Experimental Setup

In order to characterize the effect that riveted lap joints have on the power spectra of AE recorded during fatigue cycling of 7075-T6 aluminum, nine tensile specimens were cycled on the MTS machine with acoustic emission sensors attached. The two specimen configurations tested are shown in Figure 3.1. Six samples were constructed with a

![Figure 3.1 Specimen Configurations and Sensor Placement](image-url)
riveted lap joint and three without. The configuration without rivets was used during the first phase of the research, which focused on characterizing crack behavior for the selected loading.

Crack growth and rivet rubbing signals were recorded from each of the specimens by bonding a sensor next to the notch and using its output to trigger a storage oscilloscope. The oscilloscope digitized the outputs from the storage sensor over a 200 microsecond interval, which was the typical duration of an AE burst type emission in these specimens. The waveform storage sensor was a wide-band piezoelectric transducer with operating frequencies between 0.1 and 1.0 MHz, whereas the trigger sensor was resonant at 300 kHz. The two outer sensors were also resonant at 300 kHz and were used to confirm the AE source by providing linear location data. After a signal was digitized by the oscilloscope, the data were transferred in unsigned byte format to a 486DX-50 computer using a GPIB interface.

All specimens were constructed from 0.125 inch thick by 1 inch wide 7075-T6 aluminum. As seen in the detailed drawing of the joint configuration provided in Figure 3.2, eight aircraft type rivets (AN470AD-4-9) were installed in a symmetrical pattern on opposite sides of a tapered double-lap joint configuration. The joint was designed and constructed according to aircraft design specifications [24]. Each rivet hole was drilled with a 0.125 inch bit, and machined with a 30 size ream. Using a rivet gun and bucking bar, individual rivets were installed such that the shop head diameter was approximately 0.187 inches. A 0.125 inch deep notch was placed at the center of one of the tapered sections using a triangular file.

Fatigue crack initiation occurred at the notch tip and its growth was sustained for about 10,000 cycles. During experimentation, the specimens were periodically removed from the MTS and inspected with liquid penetrant and a photo-microscope to check for crack growth. Figure 3.3 shows a riveted specimen fixed to the MTS grips, and Figure 3.4 shows a picture of the crack with ×75 amplification. Plumber's putty was attached to
Pivoted Notched Specimen

Figure 3.2. Detailed Drawing of Joint Configuration
Figure 3.3. Riveted Specimen Fixed to the MTS Grips
Figure 3.4. Photograph of Crack Taken with the Photo-Microscope

(× 75 Amplification)
the ends of the specimens in order to attenuate MTS related noise and avoid false triggering of the storage oscilloscope.

Every specimen was subjected to a sinusoidal load cycle with a minimum load of 250 lbs, a maximum of 1,250 lbs, and a period of 0.6 seconds (Figure 3.5). Using standard GPIB commands combined with front end digital circuitry, the oscilloscope was programmed to standby for a trigger level crossing every time the load exceeded 80% of maximum. Since fatigue crack growth is known to occur only near maximum load, the oscilloscope was not allowed to trigger during the remainder of the cycle.

The output from each of the four sensors was connected to the LOCAN-AT. This four-channel system provided the capability of source location and stored conventional signal parameters for individual AE hits. Although the LOCAN-AT is not capable of recording individual waveforms, it provided crucial information by storing conventional parameters for discrete signals as a function of time. The settings required for correct operation of the LOCAN-AT are explained in Appendix A. Sample plots obtained from this system are shown in Figures 3.6, 3.7, and 3.8.
Figure 3.6 shows the accumulation of AE hits at different loads for the trigger sensor when it was bonded to a specimen designed to produce only crack growth emissions. An AE hit was registered by the LOCAN-AT each time a sensor output signal crossed the specified threshold level (40 dB). It can be seen that most crack growth hits occurred near the top twenty percent of the load cycle (above 1,050 lbs).

![Crack-Only Specimen](image)

Figure 3.6. Hits Versus Load Plot for Tensile Specimen Without Rivets

Figure 3.7 shows the hits versus load plot for a riveted specimen before crack initiation. Since rivet related signals were also detected near maximum load, there is a chance that crack growth and rivet rubbing events occurred simultaneously, which causes problems in locating the source of an emission. The data in Figure 3.8 were produced by a riveted specimen after crack initiation. It can be seen that a peak exists at the maximum load point, which indicates the presence of crack growth. In order to characterize signals which came from the crack tip, it was necessary to rely on linear location methods.
Figure 3.7. Hits Versus Load for a Riveted Specimen Before Crack Initiation

Figure 3.8. Hits Versus Load for a Riveted Specimen After Crack Initiation
The linear location of AE sources can be calculated if the wave speed and time of arrival at the two outer sensors is known. Because of dispersion effects associated with wave propagation in plates, the wave speed can vary significantly with frequency. However, since the two outer sensors were resonant at 300 kHz, a single wave speed was used which corresponded to that frequency. Prior to beginning experimentation the LOCAN-AT software was determined to provide correct source location when a value of $1.2 \times 10^5$ in/sec was entered as the wave speed. By producing several pencil lead breaks at different locations, the accuracy and repeatability of the system was found to be acceptable.

The location data shown in Figure 3.9 were captured by the two outer sensors when bonded to a cracked riveted specimen subjected to fatigue cycling. In order to be considered an event by the LOCAN-AT software, an AE burst signal must hit at least two sensors within a specified time interval. Although the source of several crack related

![Cracked Specimen](image)

**Figure 3.9.** Location Data Produced by Cracked Specimen
events was located properly, some of these events occurred near minimum load, which indicated that they were emitted by crack face rubbing as opposed to actual crack growth. Because different sources oftentimes emit simultaneously during cycling, several crack signals captured by the oscilloscope were not located properly by the LOCAN-AT. This introduced some uncertainty in determining the source of the emissions. However, enough crack events were located to characterize the relationship between signal parameters, and it was usually possible to identify crack growth by comparing the amplitude ratios from the trigger and storage sensors. Since the trigger sensor was placed adjacent to the crack tip, the amplitude of signals coming from crack growth was greater for the trigger sensor than for the storage sensor.

After crack initiation, three distinct possibilities needed to be considered in order to separate AE from crack growth and rivet rubbing. The first possibility was that a crack growth emission triggered the oscilloscope. The second possibility was that the oscilloscope was triggered by an emission from one of the four rivets between the trigger and storage sensors. The third possibility was that an emission from the other rivet set caused triggering. In the first case, the ratio of signal amplitudes for the trigger to the storage sensor was relatively high compared to the other two cases. This trend was confirmed by events which were successfully located with the two outer sensors. As the wave propagated through the riveted joint, the signal amplitude decreased due to dispersion and attenuation. The joint acts as a mechanical filter due to its complex geometry and the fact that there is an air gap between the plates. Attenuation due to the air gap was confirmed by applying oil to the joint in one of the specimens. Since it provided acoustic coupling between the plates, the application of oil resulted in lower attenuation levels, hence, higher signal amplitudes at the storage sensor.

In addition to crack growth and rivet rubbing, a third source was generated by lightly tapping the tip of a mechanical pencil at the notch location while the load was fixed at 1,100 lbs. This simulated source was introduced in order to verify the capability of a
neural network to distinguish between additional sources. Since the pencil taps were produced at the crack location, spectral analysis of these signals provided an indication of the effects of source location on the normalized frequency spectra.

3.2 Instrumentation

The instrumentation consisted of sensors, amplifiers, oscilloscopes, a voltage gate, the MTS load cell and signal conditioner, a digital multimeter, a computer, and the LOCAN-AT system. Figure 3.10 illustrates how the different instruments were connected and Figure 3.11 shows a photograph of the laboratory setup. The computer interfaced oscilloscope acquired data independently, while the sensors were all powered by the

Figure 3.10. Schematic of the Instrumentation Setup
Figure 3.11. Laboratory Setup
The conditioned output from the MTS load cell was sampled by both systems and used to count fatigue cycles. Load levels were transferred to the 486 computer by the digital multimeter through the IEEE-488 bus. The load signal was also monitored by an additional oscilloscope.

The output from each of the sensors was amplified by 40 dB (×100) and transferred through co-axial cables before being sampled by either the LOCAN-AT or the storage oscilloscope. The waveform storage sensor had an internal pre-amp which helped to reduce noise pickup by amplifying the signal before it left the sensor casing. The amplified output from the 300 kHz resonant sensors was somewhat noisier than that from the wide-band sensor since they were connected to external pre-amps using 3 ft long, low capacitance cables. In addition to providing signal amplification, the external pre-amps filtered the signals between 200 and 400 kHz. The output from the storage sensor was not filtered before going to the oscilloscope, however, the LOCAN-AT had an additional 200-400 kHz bandpass filter for each channel.

As seen in Figure 3.10, the output from the trigger sensor passed through a voltage gate before reaching the storage oscilloscope. By use of a voltage comparator connected to an analog switch, the voltage gate allowed the trigger signals to pass only when the load was above an adjustable reference level (1,050 lbs). During design and implementation of this circuit, extreme care was taken to reduce noise pick-up and ensure that the scope was not triggered with unwanted spikes generated by the switch each time it opened or closed. A schematic of the voltage gate circuit is shown in Figure 3.12.

The major drawback of the computer interfaced oscilloscope was that it could only record one signal per cycle. Although it is acceptable for research purposes, this system is not ideal for AE fatigue monitoring applications since multiple emissions which occasionally occurred near peak loads were not captured. This is because it took at least 0.5 seconds to transfer the data to the computer, store it in RAM, and re-arm the
oscilloscope. The limiting component in the rate of data transfer is believed to be the IEEE-488 card used for this application. The GPIB commands which controlled the scope (an HP model 54601A) were issued by a program written in Q-BASIC. The program repeatedly queried the scope to determine if it had been triggered. Once the scope was triggered, 2,000 points in the scope buffer were transferred to the computer and stored as a separate file in the computer RAM. Finally, after the buffer was emptied, a command was issued to re-arm the scope. A listing of this computer program is given in Appendix B. In order to increase the transfer speed, an 8-bit (unsigned byte) data format was selected instead of a 16-bit format. Although the 16-bit word format provides better resolution of the data, it would result in lower transfer speeds through the IEEE interface [25].

3.3 System Calibration

The transducers used were supplied with calibration data from the manufacturer, which specifies the sensitivity in decibels (dB) relative to 1 volt per microbar. Moreover, the LOCAN-AT system was periodically calibrated to ensure that it responded accurately
to a known input. Although it is good practice to work with calibrated instrumentation, absolute calibration is not crucial for obtaining reproducible results. Unless the recorded signals are used to provide a precise indication of the surface displacement and frequency of oscillation associated with each emission, it is acceptable to represent the data with respect to a reference signal as long as the reference signal is repeatable and excites a wide range of frequencies [1]. A common source of reference signals used for AE research and field testing is the pencil-lead break. If the pencil-lead is restricted to a specific type and manufacturing lot, this method has been shown to generate reproducible signals which provide a realistic simulation of typical AE sources [26].

As emphasized by Carlyle in his Ph.D. dissertation [1], calibration of AE equipment does not ensure that the results of an experiment are reproducible by other experimenters. Aware of the fact that the amplitude and frequency content of AE signals change with transducer placement, source location, and specimen geometry, Carlyle suggested a method for removing these variable effects. This task was accomplished by applying an approach similar to that proposed by Sachse and Hsu for calibrating AE transducers [27]. However, Carlyle produced a reference power spectrum corresponding to a specific sensor placement and source location and divided the spectrum into that caused by a real acoustic emission event. This method improved the flexibility of the technology by providing the means for characterizing AE spectra from crack growth in different specimens. As mentioned previously, this approach received much attention during the early 1980s when scientists around the world collaborated on efforts to test its versatility. By using a helium gas jet to generate reference signals, they compared the average frequency spectra from crack growth in 7039 aluminum using different instrumentation, loading conditions, and specimen geometries. The method was found to successfully remove variable effects and allow for true source characterization [12].

In order to correct for the effects of sensor placement and specimen geometry in the riveted specimens tested, thirty pencil lead breaks were produced at the crack location
after all sensors were in place and the load was fixed at 1,100 lbs. Unit energy spectra were obtained for each reference signal before an average calibration spectrum was determined. The average pencil lead spectra were found to vary significantly with sensor placement as a result of specimen resonances, so a new set of pencil lead spectra was produced each time a specimen was removed from the MTS grips for inspection. The lead breaks were performed at approximately 45 degrees to the surface using a Pentel mechanical pencil with 6 clicks of the lead (0.5 mm, 2H grade). Although the number of clicks and the pencil orientation was kept as constant as possible, the fact that the lead breaks were performed without consistent mechanical support required that an average spectrum be produced. Figure 3.13 shows a sample calibration set with thirty amplified signals from pencil lead breaks. Notice that there are variations between the signals, which could have reduced the effectiveness of this method in correcting for system variables. A unit energy power spectrum was calculated for each of the thirty signals, and then an average spectrum was obtained. Figure 3.14 shows the corresponding average pencil-lead spectrum in decibels relative to 1 microvolt at the sensor.
Figure 3.13. Sample Calibration Set from Pencil-Lead Breaks
Figure 3.14. Average Pencil-Lead Power Spectrum in Decibels Relative to 1 Microvolt at the Sensor
CHAPTER 4
SIGNAL PROCESSING

This chapter begins with a brief discussion of the cautions necessary when performing power spectral analysis. Next, a description is provided of the data normalization and preparation for neural network implementation.

Proper application of digital signal processing requires careful consideration of the data acquisition method employed, knowledge of the types of signals recorded, and an understanding of the calculations performed. The method utilized in this research can be summarized by stating that amplified AE signals were digitally sampled at 10 MHz over a 200 microsecond interval and later imported into digital signal processing software for spectral analysis.

4.1 Spectral Analysis

An important consideration in digital spectral analysis is the suitability of the recording instrument for providing an accurate representation of incoming analog signals. Several errors can arise from improper digital sampling which can make spectral analysis difficult or even impossible [1]. Errors associated with improper sampling aperture, variations in time intervals between samples (jitter), and instrument non-linearities were automatically accounted for in this research by utilizing a storage oscilloscope known to be appropriate for this application [25].

The next consideration in data acquisition is the selection of an adequate sampling rate. If the sampling rate is too low, higher frequency components will be lost and the overall signal will be distorted due to aliasing. Figure 4.1 illustrates how a low sampling
In order for a signal to be accurately analyzed using Fourier analysis, it is necessary that the sampling rate be at least two times greater than the highest frequency component of the signal. This condition, which is described by the Nyquist theorem [28], assures that each period of the signal is represented by at least two points. Since the broad-band sensor used to collect AE signals was sensitive up to 1 MHz, a sampling rate of at least 2 MHz would be adequate for frequency analysis. However, since a low-pass filter was not used and a precise representation of the signal was desired, a sampling rate of 10 MHz was selected. This assured that frequency components below 5 MHz did not cause aliasing in the frequency band of interest (0.2 - 1 MHz).

Increasing the sampling rate improves the resolution of the recorded signal, but it does not eliminate aliasing completely. It must be noted that pre-amp noise will be aliased since it occurs above the Nyquist frequency. This distortion is minor if the signal-to-noise ratio is high; however, it becomes a serious problem when the signal amplitude approaches the pre-amp noise level. In order to avoid significant errors associated with aliasing of pre-amp noise, only the signals with relatively high signal-to-noise ratios were selected for analysis. The quality of the digitized data can be improved by filtering the analog signals.
before sampling occurs. If employed, an antialiasing low-pass filter should be designed such that it attenuates the signal by at least 20 dB at the Nyquist frequency [28].

Although it is desirable to obtain the highest precision possible when digitizing AE signals, there was a tradeoff associated with the use of a high sampling rate. The oscilloscope utilized was capable of storing a maximum of 2,000 points in its buffer, which meant that as the sampling rate increased, the duration of the sweep decreased. For example, a sampling rate of 10 MHz provided a sweep of 200 microseconds, whereas at 5 MHz, 400 microseconds of data would be sampled. In some instances, the signal duration of the experimental waveforms were slightly greater than 200 microseconds, so it would have been advantageous to decrease the sampling rate to 5 MHz in order to capture the entire transient. The sampling rate was not changed during experimentation to avoid introducing additional variables in the data.

When a waveform is digitized and a non-integral number of periods are sampled, leakage occurs [1]. The leakage effect causes the energy under a specific frequency to spread out in the power spectrum. For example, if a 100 kHz sine wave is digitized such that the beginning and ending points are equal, the power spectrum of the signal will consist of a sharp spike at that frequency. If the beginning point is different from the ending point, however, leakage occurs and the spike at 100 kHz spreads out as shown in Figure 4.2. When digitizing AE waveforms, it is desirable to capture the entire transient in order to assure that the beginning and ending points are approximately equal to the base voltage. When the duration of the transient is greater than the sampling time, the ending and beginning points will often be different. To reduce leakage effects in this case, a windowing technique can be used.

There are several different types of windowing techniques available which force the beginning and ending points of the signal to be equal [29]. Although these methods
are effective in reducing energy leakage into adjacent frequencies, they tend to broaden the peaks and reduce the overall resolution of the spectrum. Therefore, it is better to record the entire transient and avoid the use of windowing [1].

In this thesis, spectral analysis was performed by employing a fast Fourier transform (FFT) to calculate the power spectrum of individual signals using the DADiSP software package. The input series consisted of 1,849 samples, and the output power spectrum was defined by 150 points between 0.2 and 1.0 MHz. Signals of various known frequencies were recorded from a function generator and used to assure that the power spectral calculations were accurate. The quality of the results and the speed of calculation could have been improved by more careful selection of the input data format and the FFT routine employed. However, limited resources at the time resulted in the selection of the
first method which produced acceptable results.

4.2 Data Normalization and Reduction

The data processing portion of this research involved the representation of individual time-domain AE signals as normalized frequency spectra suitable for neural network processing. The use of a digital signal processing software package (DADiSP) provided a visual display of the data analysis process and allowed for easy manipulation of individual signals without the need for extensive programming. Figure 4.3 shows the analysis worksheet used to normalize and prepare the data for neural network implementation.

Figure 4.3. Data Analysis Worksheet in DADiSP
Data processing was performed automatically by running batch files written in the DADiSP language specifically for this application. First, the time-domain signals recorded during a given test were copied from the hard drive onto a virtual drive (RAM) together with a corresponding average pencil-lead calibration spectrum. The second step was to import the pencil-lead spectrum into Window 5 of the worksheet. Next, a time-domain signal was imported into Window 1, and a resulting 25-point spectrum was written to the virtual drive. After all time-domain signals for a given test were processed, the data was saved as a collection of files in a separate directory on the computer hard drive.

Once a time-domain signal was imported into Window 1, several calculations were automatically performed by the worksheet before a 25-point spectrum was written to the virtual drive. Window 2 scaled and extracted the portion of interest from the raw time-domain signal in Window 1 to prepare it for the FFT calculation. Window 3 calculated the power spectrum of Window 2, and then Window 4 normalized it to unit energy. Windows 6 and 7 extracted the frequency range between 0.2 and 1.0 MHz from the spectra in Windows 4 and 5. Next, Window 8 performed a point by point spectral division of window 6 by Window 7 and represented the result on a relative log scale. Finally, Window 9 reduced the 150-point spectrum in Window 8 to a 25-point spectrum by calculating the area under 25 equal frequency bands between 0.2 and 1.0 MHz. The result of Window 9 was arranged as an ASCII file of numbers and was written to the virtual drive. Window 10 provided a visual representation of the end result.

The data processing scheme described above was performed on a total of 1,311 signals for which the source was known. In order to use the data for neural network implementation, the category of each signal was labeled and the data was merged into groups for training and testing purposes. For the present, it is sufficient to describe these files as a collection of ASCII numbers, with each row corresponding to a specific signal. Chapter 5 provides a more detailed description of how these files were utilized to train and test the neural networks.
CHAPTER 5
NEURAL NETWORK CLASSIFICATION

This chapter covers some of the theory behind neural network architecture and operation as it relates to signal pattern classification. The first network discussed is the Kohonen self-organizing map, which is especially useful for classifying signals for which the sources are unknown. The back-propagation neural network is discussed next. It is a more powerful classifier when information about the origin of each signal is known prior to training.

The neural networks utilized in this research were developed using a commercially available applications software package called NeuralWorks Professional II/Plus. The explanations which follow are based primarily on information provided in the software manuals [30], but also include references to other sources [31-34].

5.1 General Overview

Neural networks are basic computer algorithms which attempt to model functions of the brain such as recognizing patterns, forming associations, and learning from experience. The human brain consists of billions of interconnected neurons, and there is no existing computer which can even come close to matching its complexity and versatility. Although they are much simpler than the human brain, the advantage of computer-based neural networks is that they can consistently process a large amount of data and automatically perform functions which would require the analysis of an expert.

The most important characteristic of neural networks is their ability to learn from examples. During the learning phase, a network modifies the connections between individual processing elements such that a specific output is produced in response to a
A fundamental characteristic of any network is the learning rule used to adjust the weight of each connection. When the desired response to an input is specified, the network is said to perform supervised learning, whereas, when the desired response is not specified, the process is referred to as unsupervised learning or self-organization.

In order to check how well a network has learned to recognize a desired pattern, its performance must be tested with known inputs. A combination of training and testing is required for successful neural network implementation. To assure that a network has trained properly, the testing phase must be performed with examples that the network has never seen before. Once it is capable of consistently identifying patterns which are similar, but not identical, the network is said to be trained. Considering the random nature of AE signals, the flexibility in classification of a neural network to variations between different inputs of the same category is a very important requirement.

There are several types of neural network architecture which differ in their structure and internal mathematics. The selection of a particular network is generally based on the application requirements, but may also be governed by cost of development and time constraints. For signal pattern classification, the self-organizing map and the back-propagation networks are popular selections. Back-propagation networks are well known for their ability to solve non-linear classification problems with high execution speeds. However, development time and cost in certain applications is relatively high since back-propagation networks require supervised training. The data requirements and training time are lower for self-organizing maps since they do not require the user to define the output that each training example should produce.

5.2 Self Organizing Map

The self-organizing map (SOM) creates a two-dimensional feature space from an n-dimensional input space. For example, if two input signals are similar, they will be mapped close together on the two-dimensional feature map. The SOM network was
devised by Teuvo Kohonen of the Helsinki Technical University in Finland [31]. Its ability to classify input patterns internally makes it a useful tool for automatically sorting a large number of items into categories. The classification capability of SOM networks has been used as a front end to other neural network architectures such as back-propagation. Although powerful prediction and pattern recognition networks can result from the combination of self-organization and supervised training [30], such a scheme was not attempted in this research.

The SOM network used herein had an input layer of 25 neurons which were fully connected to a two-dimensional competitive layer as shown in Figure 5.1. The neurons in the competitive layer were not connected to each other, but to an output which indicated the coordinates of the winning neuron. Each neuron in the competitive layer measured the Euclidean distance of its weights to the incoming input quantities, and the neuron with the smallest distance was considered the winner. The winning neuron had an output of one, whereas all the other neurons had an output of zero.

![Figure 5.1. Structure of the SOM Network Utilized](image-url)
If the 25 input values are denoted by
\[ X = (x_1, x_2, \ldots, x_{25}) , \]
and the corresponding weights of each connection are given by
\[ W = (w_1, w_2, \ldots, w_{25}) , \]
then the Euclidean distance is defined as
\[
D = \| X - W \| = \sqrt{(x_1 - w_1)^2 + (x_2 - w_2)^2 + \cdots + (x_{25} - w_{25})^2}
\]

During the learning phase the Euclidean distances were adjusted by a conscience mechanism in order to avoid single neurons from representing too much of the input data. This could occur if the initial values of the weights connecting to a specific neuron isolate it from the training process. The conscience mechanism keeps track of how often each neuron wins and makes adjustments to prevent a given neuron from winning too much. This process helps to spread the categories more efficiently on the feature space, providing finer discrimination between existing classes. The adjusted distance was given by the original distance \( D \) minus the corresponding bias \( B_i \), which was computed using
\[
B_i = \gamma(N - F_i - 1) \quad i = (1, 2, \ldots, 25) ,
\]
where \( F_i \) is the frequency with which a specific neuron won, and \( N \) is the total number of neurons in the competitive layer. The value of \( \gamma \) is referred to as the conscience coefficient since it regulates the amount by which the distances are adjusted. For the SOM network used here, \( \gamma \) was kept at 0.9 throughout training. The value of \( F_i \) was updated according to the expression
\[
F_{i, \text{new}} = F_{i, \text{old}} + \beta(1 - F_{i, \text{old}})
\]
for the winning neuron, and by
for all other neurons in the competitive layer. The quantity \( \beta \) is referred to as the frequency estimate coefficient. Its value was fixed at 0.15.

In addition to adjusting the Euclidean distances, the weights of specific neurons were also adjusted during training according to the following relation:

\[
F_{i, \text{new}} = F_{i, \text{old}} + \beta(-F_{i, \text{old}})
\]

where \( \alpha \) is the learning coefficient. The magnitude of \( \alpha \) was specified as 0.2 at the beginning of training and decreased by a factor of 0.7 after every 10,000 counts during a total of 800,000 training counts. Each count corresponds to the presentation of a single example from the training set. The formula for adjusting the weights was applied to the neurons in the neighborhood of the winner. At the beginning of training, the neighborhood included 64 neurons forming a square pattern around the winner. As training progressed, the neighborhood size was decreased gradually until it included only the eight neurons immediately adjacent to the winner as shown in Figure 5.2.
In order to increase the resolution of the two-dimensional feature map, an interpolation option was selected. The NeuralWorks implementation of SOM networks uses the three lowest Euclidean distances from the input vector to determine a coordinate value which lies between neurons in the competitive layer. This method provides a more precise coordinate determination by distinguishing between the location of two input vectors which excite the same winning neuron. A more detailed description of the interpolation method used can be found in the NeuralWorks Professional II/PLUS software manual [30].

The input data used to train the SOM network consisted of a series of ASCII numbers with each row of 25 numbers representing a separate waveform. The actual value of each number was normalized automatically by NeuralWorks in order to match the software data requirements. Once a normalized dataset was created, each input pattern was presented to the network in an orderly fashion.

An epoch size of twenty was selected, which means that the weight adjustments were accumulated in memory and the actual weight values were changed only after twenty examples were presented to the network. The use of a relatively large epoch ensures that the learning process proceeds more efficiently, but if the epoch is too large the network may never train [30].

The results obtained with the SOM configuration described above are discussed in Chapter 6. Although some variations of the network were attempted, the results presented are for a single configuration. Improvement in network performance could be obtained by analyzing more closely the effects of changing parameters such as neighborhood shape, conscience and learning coefficients, and the number of neurons in the competitive layer.
5.3 Back-Propagation

The back-propagation network is a modern neural computing technique which is capable of solving non-linear classification problems [30-34]. A typical back-propagation network has an input layer, an output layer, and at least one hidden layer. As shown in Figure 5.3 the back-propagation network utilized in this research consisted of 25 neurons in the input layer, 20 neurons in a single hidden layer, and 3 output neurons. Training of back-propagation networks involves defining the desired output to a given input pattern and using the resulting error in classification to adjust the weights of individual connections such that the global error is reduced. This process is repeated for the entire training set until the global error is decreased to an acceptable level defined by the user. Once the network is considered trained, it is tested with a new set of examples to evaluate its performance.

Figure 5.3. The Back-Propagation Neural Network Utilized
The format of the training dataset was similar to that for the SOM network; however, each example was followed by a binary number (Figure 5.3) representing the desired output. The input data were normalized by NeuralWorks and presented to the network in random order using a function called "shuffle and deal." This process was required so that learning could proceed in a stable manner, without large shifts in the global error.

The neurons in the input layer were fully interconnected with those in the hidden layer, and each neuron in the hidden layer was also connected to the three output neurons. Moreover, every neuron in the hidden and output layers was connected to a bias neuron which insured that the output quantities remained within acceptable limits in order to speed up the learning process. When the normalized input data was first presented to the network, the information was transferred to the hidden layer through each of the 500 connections (25 input neurons with 20 connections per neuron). Then, each neuron in the hidden layer performed the following operation before transferring its output to the next layer:

\[ x_j = f(z) \cdot \sum_i (w_{ji} \cdot x_i) = f(z) \cdot I_j \]

where

\[ i = (1, 2, \ldots, 25) \]

\[ j = (1, 2, \ldots, 20) \]

\[ f(z) = (1 + e^{-z})^{-1} \]

As seen in Figure 5.4, \( x_i \) is the value of each input neuron, \( w_{ji} \) is the weight of each connection, \( x_j \) is the output of each neuron in the hidden layer, and \( f(z) \) is a differentiable transfer function (which was selected to be the sigmoid function for this application).

The information transferred from neurons in the hidden layer was processed in the same manner by the neurons in the output layer such that three numbers were generated at
the output level. The error between the actual and the desired outputs was then used to generate an increment or decrement in the weight of each connection in order to decrease the global error. The global error $E$ was back-propagated through the network layers by applying the delta learning rule:

$$E = 0.5 \sum_k (d_k - a_k)^2 \quad k = (1, 2, 3),$$

where $d_k$ is the desired value of each neuron in the output layer, and $a_k$ is the actual value obtained after each pass. The local error at each neuron is defined by

$$e_j = -\frac{\partial E}{\partial I_j}.$$

Since the transfer function was a sigmoid, the local error $e_j$ for each neuron in the hidden layer was given by

$$e_j = x_j \cdot (1 - x_j) \cdot \sum_k (e_k \cdot w_{kj}).$$

This quantity was used to adjust the weights of individual connections according to the relation

$$\Delta w_{ji} = \alpha \cdot e_j \cdot x_i + m \cdot \Delta w_{ji},$$
where $\alpha$ is the learning coefficient, and $m$ is the momentum term. In order to reduce the training time and ensure stability, the learning coefficient and momentum term were varied during training according to the schedule given in Table 5.1. For most efficient training, it is recommended that the learning coefficient of the hidden layer be greater than that for the output layer, and that both the learning coefficient and momentum approach zero as training progresses [30].

Table 5.1. Learning Schedule Used for this Application

<table>
<thead>
<tr>
<th>Learning Count</th>
<th>300,000</th>
<th>500,000</th>
<th>700,000</th>
<th>1,100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden Layer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning Coefficient</td>
<td>0.1</td>
<td>0.06</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Momentum Term</td>
<td>0.1</td>
<td>0.07</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Output Layer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning Coefficient</td>
<td>0.08</td>
<td>0.05</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Momentum Term</td>
<td>0.1</td>
<td>0.05</td>
<td>0.025</td>
<td>0.02</td>
</tr>
</tbody>
</table>

The connection weights of the network were updated after several examples were presented at the input level. This method is referred to as cumulative back-propagation because the delta weights corresponding to each example are accumulated until the entire epoch is presented. By trial and error, it was found that an epoch size of twenty waveforms lead to fastest training of the network.

Another mechanism which reduces training time and improves network performance is the Softmax Activation Function. A detailed explanation of the equations
involved is provided in the software manual [30]. Since the Softmax function forces the output sum to equal 1, it is very useful for classification problems in which the desired output is of the form

\[ d = (0, ..., 1, ..., 0) \]

This type of output is referred to as a "one of N" code since only the neuron corresponding to a desired class has a non-zero value equal to one. This was the case with the classification problem at hand, where crack growth was denoted by (1,0,0), rivet rubbing by (0,1,0), and pencil taps by (0,0,1). By implementing the Softmax function, the network was forced to decide on a specific category, thus improving its functionality.
CHAPTER 6
DISCUSSION

This chapter presents the final results and discusses some important observations and recommendations for other experimenters who wish to pursue research with similar objectives. Finally, it describes the applications and potential developments of this work.

6.1 Results

After testing six riveted specimens as described in Chapter 3, a total of 1,311 signals were selected for neural network implementation. Table 6.1 summarizes the results for the data acquisition portion of this research. As can be seen, most of the crack growth signals came from specimens 2, 3, and 4, whereas most of the rivet rubbing signals came from specimens 1, 4, and 6. The number of signals collected from each of these two categories varied largely for different specimens. As indicated in the table, the number of cycles to crack initiation and final crack length were also significantly different for each specimen. This large variation was perhaps a result of differences in the sharpness of the notches or variations in the distribution of the stresses through the joints. Specimens 1 and 5 took much longer to crack and sustained the crack for longer than specimens 2, 3, and 4. The crack in specimen 2, on the other hand, advanced very quickly, although it did not produce as many crack growth signals as specimen 3. Specimens 2 and 3 were tested for crack growth only, while a crack was not initiated in specimen 6. Moreover, pencil taps were produced only in specimens 1, 4, and 5.

Individual signals were selected based on time-of-arrival, amplitude, and signal-to-noise ratio, as discussed previously. Figure 6.1 shows sample signals from each category together with their corresponding 25-point spectra. All three signals shown were
### Table 6.1 Summary of Data Acquisition Results

<table>
<thead>
<tr>
<th>Specimen Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Crack Growth Signals Used</td>
<td>27</td>
<td>199</td>
<td>245</td>
<td>116</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>Total Number of Rivet Rubbing Signals Used</td>
<td>247</td>
<td>0</td>
<td>0</td>
<td>176</td>
<td>11</td>
<td>70</td>
</tr>
<tr>
<td>Total Number of Pencil Tap Signals Used</td>
<td>83</td>
<td>0</td>
<td>0</td>
<td>60</td>
<td>69</td>
<td>0</td>
</tr>
<tr>
<td>Number of Crack Growth Signals Used for Training</td>
<td>9</td>
<td>42</td>
<td>63</td>
<td>13</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Number of Rivet Rubbing Signals Used for Training</td>
<td>63</td>
<td>0</td>
<td>0</td>
<td>42</td>
<td>6</td>
<td>26</td>
</tr>
<tr>
<td>Number of Pencil Tap Signals Used for Training</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>24</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>Number of Average Pencil Lead Spectra Produced</td>
<td>7</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Approximate Cycles Before Crack Initiation</td>
<td>$8.5 \times 10^4$</td>
<td>$3.0 \times 10^4$</td>
<td>$4.2 \times 10^4$</td>
<td>$2.4 \times 10^4$</td>
<td>$7.5 \times 10^4$</td>
<td>$-$</td>
</tr>
<tr>
<td>Total Number of Cycles</td>
<td>$9.2 \times 10^4$</td>
<td>$4.5 \times 10^4$</td>
<td>$5.1 \times 10^4$</td>
<td>$3.5 \times 10^4$</td>
<td>$8.2 \times 10^4$</td>
<td>$1.5 \times 10^4$</td>
</tr>
<tr>
<td>Final Crack Length (in)</td>
<td>0.045</td>
<td>0.195</td>
<td>0.048</td>
<td>0.105</td>
<td>0.007</td>
<td>$-$</td>
</tr>
</tbody>
</table>
collected from specimen 4 and were normalized using the same reference pencil-lead spectrum. Notice that the general shape of the 25-point spectra are similar for crack growth and the pencil tap. This similarity indicates that information on source location is carried by the normalized spectra. Even though the crack growth and pencil tap spectra appeared to be similar at first glance, distinct differences could be identified through close inspection. It must be noted, however, that the 25-point spectra varied significantly for different specimens, which raised some doubts about the effectiveness of the pencil-lead breaks in completely removing system variables.

![Recorded Signal and 25-Point Spectrum](image)

**Figure 6.1.** Sample Waveform and Corresponding 25-Point Spectra from Each Category
In the hope of obtaining cluster separation between the three classification categories, the SOM neural network was trained with all 1,311 signals. Figure 6.2 shows the result obtained for a SOM network with 25 input neurons and a 15 by 15 array of neurons in the competitive layer. Although there was considerable overlap between the different classes, separate regions could be associated with each category. The triangles in the lower right-hand corner correspond to pencil taps, the three separate clusters of crosses correspond to rivet rubbing, and the clusters of squares correspond to crack growth. The fact that clusters from the same category occupied different regions in the feature map suggests that individual signals from the same type of source can vary significantly.

Closer analysis of the results indicated that the SOM network classified the signals based on which specimen emitted them. To a certain extent, this was expected since

![Figure 6.2. Result of SOM Network Classification for Six Specimens Tested](image-url)
emissions from different cracks or rivets are known to vary significantly. Each specimen will distribute stresses differently among the rivets, and likewise, each crack will grow with a distinct orientation and rate. There is also the possibility, however, that the effects of system variables were not removed completely by the data normalization scheme. The data from pencil taps serve as an indication that this may have been the case. Pencil taps were generated in three of the six specimens, with 83 events from the first specimen, 69 from the second and 60 from the third. Since three distinct clusters of triangles corresponding to each specimen were grouped in the lower right-hand corner of the map (Figure 6.2), it is clear that the variable effects of sensor placement and specimen geometry were not completely removed. On the other hand, the fact that the three triangle clusters are adjacent to each other on the feature space indicates that variable effects were partially removed.

In order to get a better picture of how each category clusters on a feature map, another SOM network was trained, but this time, with data from specimen 4 only. The results (Figure 6.3) indicate that better separation between the three categories can be obtained for a single specimen.

![Figure 6.3 Result of SOM Network Classification for Specimen 4 Only](image)
By performing unsupervised training, the SOM network tends to organize signals based on the more obvious features of the data such as those related to specimen geometry and sensor placement. By performing supervised training with a back-propagation network, one can force the network to overlook these unwanted features and concentrate on the distinctive ones. The back-propagation network used here consisted of 25 inputs, 20 hidden neurons, and 3 outputs. Table 6.2 shows the number of signals which were used for training and testing purposes. With a total of 343 examples in the training set, the backpropagation network was allowed to learn for $1.5 \times 10^6$ counts.

Table 6.2. Training and Testing Files Used for Neural Network Implementation

<table>
<thead>
<tr>
<th>Source</th>
<th>Total</th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crack Growth</td>
<td>595</td>
<td>132</td>
<td>463</td>
</tr>
<tr>
<td>Rivet Rubbing</td>
<td>504</td>
<td>137</td>
<td>367</td>
</tr>
<tr>
<td>Pencil Taps</td>
<td>212</td>
<td>74</td>
<td>138</td>
</tr>
</tbody>
</table>

Once the rms error level was below 1%, the network was tested with a total of 968 signals. Table 6.3 gives the final results obtained during the testing phase. As can be seen, the network classified the source of individual signals correctly 94% of the time for crack growth, 99% for rivet rubbing, and 96% for pencil taps. Of the total number of mistakes made in classifying crack growth signals, 64% involved classification as rivet rubbing, and 36% involved classification as a pencil tap. From the mistakes made in
classifying pencil taps, 50% involved classification as crack growth and 50% as rivet rubbing. With the rivet rubbing test data, two mistakes involved classification as crack growth and one as a pencil tap.

Table 6.3 Final Results for Neural Network Classification

<table>
<thead>
<tr>
<th></th>
<th>Number of Mistakes</th>
<th>Percent Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crack Growth</td>
<td>28</td>
<td>94</td>
</tr>
<tr>
<td>Rivet Rubbing</td>
<td>3</td>
<td>99</td>
</tr>
<tr>
<td>Pencil Taps</td>
<td>6</td>
<td>96</td>
</tr>
</tbody>
</table>

6.2 Conclusions

The primary intent of this thesis was to demonstrate the capability of detecting individual crack growth signals emitted from a riveted joint during fatigue cycling. By implementing a back-propagation neural network to provide automatic pattern classification, it was possible to discriminate between individual signals emitted from crack growth, rivet rubbing, and pencil taps based solely on their frequency content.

The results obtained with the Kohonen self-organizing map indicated that signals from the same type of source varied significantly, especially for different specimens. This observation can be attributed to the random nature of AE signals which results from differences in load paths, random distribution of inclusion particles, and variations in the location, orientation, and characteristics of each source. Although there was overlap...
between the clusters formed by the self organizing network, limited pattern classification can still be extracted from the feature space.

Lack of repeatability of the reference pencil-lead spectra was another factor which contributed to variations among signals from the same category. The reference spectra were used to correct individual AE signals for the effects associated with transducer placement and wave propagation. Successful application of this method relies on the quality of the reference spectra, and to some extent, on how well the reference waveforms simulated the propagation of an AE waveform. Because the pencil-lead breaks were performed without mechanical support, there was considerable variation between the individual calibration signals. The lack of repeatability could also have been caused by variations in the characteristics of the different leads used. Since a large amount of lead (0.5 mm, 2H grade) was utilized during testing, it was necessary to use different manufacturing batches. Another probable explanation for the variation in reference signals is that the tip of the mechanical pencil was damaged during experimentation. Since the lead often breaks at the metal tip of the pencil, any change in the shape of that support could influence the manner in which the lead breaks.

Despite problems in removing system variables and the random nature of recorded AE, the back-propagation network provided effective classification of signals in all six specimens tested. In order to generate a trained network which was flexible enough to identify individual AE signals, a large training set was required. Moreover, it was necessary to train the network with signals from different specimens. Due to the large scatter in the features associated with each category, the network was required to train through $1.5 \times 10^6$ counts before an acceptable error level was attained. Once training was complete, the network provided accurate pattern classification very quickly. This characteristic of back-propagation networks makes them well suited for real-time applications.
6.3 Recommendations

The back-propagation neural network implemented in this research was relatively simple in that it had only one hidden layer and did not incorporate a front-end self-organizing layer. It is believed that by adding another hidden layer, the classification capability of the network would increase. Networks with two hidden layers can perform more general classification by mapping features which are normally excluded by single-layer networks [35]. Improvement in network performance may also be obtained by first projecting the input patterns onto a competitive layer and training the back-propagation paradigms with interpolated coordinate outputs from the feature space. Such an architecture is found in the counter-propagation network [30]. Implementation of additional features may be necessary when applying neural networks to more complex situations. Another recommendation is to include the use of different specimen geometries and loading conditions in the training set, in order to obtain a more generalized classifier. It is also important to verify how well the method applies to structures of different materials.

In addition to implementing superior classification methods, more effort needs to be devoted to understanding the nature of the variations between signals of each category. This could be achieved by performing detailed statistical analyses of the data and developing theoretical models of the source mechanisms and wave propagation in riveted joints. Furthermore, the quality of the data could be enhanced by paying closer attention to improving the repeatability of the reference calibration signals and increasing the precision of the data. The resolution of the calculated power spectra could be improved by sampling the signals for a longer interval in order to increase the chances of capturing the entire transient and avoid leakage effects. Moreover, better signal-to-noise ratio could be obtained by implementing a low-pass filter to avoid aliasing of pre-amp noise in the recorded signals. Finally, 16-bit data resolution and faster data storage rates could be obtained by utilizing more sophisticated instrumentation.
Although this research has shown the feasibility of using neural networks to detect crack growth in riveted joints, the proposed method is limited since it relies on triggering logic and timing parameters in order to generate snapshots of AE transients. For further research, it would be desirable to implement a neural network which can provide pattern classification from a continuous signal. The approach would be similar to that used in continuous speech recognition, where the beginning and ending of words are not well defined. A type of neural computing technique called spatiotemporal pattern recognizer has been developed for such applications. Instead of using conventional n-dimensional feature vectors to define patterns, the spatiotemporal pattern is represented by a trajectory in n-dimensional space of a vector parameterized by time. These networks represent the leading edge of neural computing technology and are considerably more complicated than conventional neural networks [32].

6.4 Potential Developments

Given the current advances in high speed neural chips, the capability of automatically classifying individual AE signals into appropriate categories can be developed into powerful real-time monitoring systems. Such systems could be packaged into a small intelligent sensor which performs all calculations necessary to provide automatic crack detection in critical structural components. Because of their low weight and immunity to structural noise, these intelligent sensors would be particularly well suited for monitoring aircraft structures.

Neural chips are becoming available with remarkable features such as 1 Mbit of memory storage, 1.2 billion 8-bit or 40 million 32-bit multiplications and additions per second, and high temperature resistance [36]. Such devices are well suited for AE pattern classification since they are capable of performing fast Fourier transforms and neural network pattern recognition in real time with high accuracy. When "hot wired" to sensors
and developed as stand alone units, these chips can provide real-time pattern recognition very efficiently and at a much lower cost than conventional computer platforms [37]. Such devices could be installed permanently on aging structures to provide monitoring of critical areas.

Another application would be to implement the neural network and signal processing scheme described in this thesis as a front-end device in conventional AE systems. Such a device could be used to classify individual signals into appropriate categories by providing a digital output to be stored together with signal parameters. If combined with this additional feature, the versatility and reliability of commercial AE systems could be improved significantly.
APPENDIX A
LOCAN-AT SYSTEM TIMING PARAMETERS

This appendix defines the LOCAN-AT timing parameters and provides the values used for this research. More detailed definitions and methods for selecting timing parameters are provided in the LOCAN-AT user’s manual [38]. Before performing any test with the LOCAN-AT, it is necessary to select appropriate values for the Peak Definition Time (PDT), Hit Definition Time (HDT), and the Hit Lockout Time (HLT).

The PDT value establishes the time (in microseconds) which the system must wait before it defines the true peak of a given signal. This time interval should be as short as possible, but long enough to avoid false measurements on waveform precursors.

The HDT value must be defined such that the system can determine the end of a given hit. The HDT should also be set as short as possible in order to allow high data throughput rates and prevent separate events from being treated as a single hit. If the HDT is too short, however, a single event may be represented by several hits.

The HLT defines the re-arming time of the system. Proper adjustment of the HLT parameter allows the experimenter to avoid making measurements of wave reflections and late arrivals. The HLT should be as short as possible if wave reflections are not a problem. The timing parameter values used for this research are given below:

$\text{PDT} = 150 \ \text{microseconds}$

$\text{HDT} = 300 \ \text{microseconds}$

$\text{HLT} = 1000 \ \text{microseconds}$
This QBASIC program uses an IEEE-488 to interface a Kiethley 197 DMM and a HP 54601A digital oscilloscope to an IBM 486DX-50 computer. The program acquires acoustic emission waveform data near the point of maximum load during fatigue cycling and stores them on a RAM disk.

Program written by Adriano Almeida and Glenn Greiner Summer B 1993

```
OPTION BASE 1
DIM wave$(4000)

'Configure Personnal488 card
OPEN "\DEV\IEEEOUT" FOR OUTPUT AS #1
IOCTL #1, "BREAK" 'reset gpib card
PRINT #1, "RESET"
OPEN "\DEV\IEEEIN" FOR INPUT AS #2
PRINT #1, "FILL ERROR"
ON ERROR GOTO ieeer
PRINT #1, "ERROR OFF"

'Configure Keithley 197 Digital Multi Meter (Address 20)
'sets default configuration function, range front panel
'relative off, db off trigger continuous on talk data format
'with prefix EOI enabled, srq terminator carriage return
'data logger disabled

PRINT #1, "OUTPUT 20, CLEAR"
PRINT #1, "REMOTE 20"
PRINT #1, "OUTPUT 20, T1X"

'Configure HP 54601A Oscilloscope (Address 07)
'Reset scope to default, see page 7-14 of HP manual for
details on default values
```
PRINT #1, "OUTPUT 07, *RST"
PRINT #1, "OUTPUT 07, TIM RANG 2 MS, REF LEFT"
PRINT #1, "OUTPUT 07, TRIG MODE SINGLE, SOUR CHAN2, LEV 12.5 mV"
PRINT #1, "OUTPUT 07, CHAN1 COUP AC, RANG 16 V"
PRINT #1, "OUTPUT 07, CHAN2 COUP AC, RANG 16 V"
PRINT #1, "OUTPUT 07, ACQ TYPE NORMAL, COMPLETE 80"
PRINT #1, "OUTPUT 07, DITHER OFF"

This loop keeps reading DMM until the voltage exceeds a defined level. Once the level is exceeded, the scope is enabled.

cycle = 0
nw = 0
dmm

PRINT #1, "OUTPUT 07, STOP"
vtlvl = 0
WHILE vtlvl < 68
  PRINT #1, "ENTER 20"; 'reads voltage from DMM
  INPUT #2, V$
  vtlvl = VAL(MID$(V$, 5, LEN(V$)))
WEND

The RUN statement configures the scope to wait for a trigger level exceedance so that it can store the signal in case it occurs. The loop keeps checking if the scope has triggered while it also checks the voltmeter reading. Once trigger occurs, the waveform is stored by (waveget) If the scope is not triggered before the voltage drops below 90%, the scope is stopped and the program is returned to dmm.

trigger
PRINT #1, "OUTPUT 07, run"
WHILE vtlvl >= 0
  IF vtlvl < 7 THEN flag = 0
  PRINT #1, "OUTPUT 07, *CLS"
  PRINT #1, "OUTPUT 07, *ESE 2" 'enables trigger register'
  PRINT #1, "OUTPUT 07, TER?" 'queries trigger event
  PRINT #1, "ENTER 07"
  vtwave = 0
  WHILE IOCTL$(2) = "1"
    vttrg = VAL(INPUTS$(1, 2))
    IF vttrg = 1 THEN vtwave = 1
  WEND
IF vtwave = 1 THEN GOTO waveget

PRINT #1, "ENTER 20"  'read voltage from dmm
INPUT #2, v$
vtlvl = VAL(MIDS(v$, 5, LEN(v$)))
IF vtlvl > 7 THEN GOSUB count
WEND

'**********************************************************************
'These commands digitize and store the waveform in channel 1 on
'the virtual disk D

waveget
nw = nw + 1
OPEN "A", 3, "D\COUNT DAT"
PRINT #3, "wave", nw, " at cycle", cycle, "load=" , v$
CLOSE #3
file$ = "D\wave" + LTRIM$(STR$(nw)) + " dat"
OPEN "O", 4, file$
iw = 0
PRINT #1, "OUTPUT 07, WAV POIN 2000,FORM BYTE, SOUR CHAN1"
PRINT #1, "OUTPUT 07, WAV DATA?"
PRINT #1, "ENTER 07"
WHILE IOCTL$(2) = "1"
  iw = iw + 1
  wave$(iw) = INPUT$(1, 2)
  PRINT #4, wave$(iw),
WEND
CLOSE #4
PRINT "wave", nw, " at cycle", cycle
IF nw = 100 THEN STOP
GOTO trigger

ieeer
IOCTL #1, "BREAK"
PRINT #1, "STATUS"
INPUT #2, ST$
PRINT CHR$(7), "Error ", MID$(ST$, 15, 2), ", ", MID$(ST$, 27)
STOP RESUME NEXT
END

count
IF flag = 0 THEN cycle = cycle + 1
flag = 1
RETURN
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