An Artificial Intelligence Approach to Fatigue Crack Length Estimation From Acoustic Emission Signals

Shane T. Ennis
AN ARTIFICIAL INTELLIGENCE APPROACH TO FATIGUE CRACK LENGTH ESTIMATION FROM ACOUSTIC EMISSION SIGNALS

by

Shane T. Ennis

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Accepted by:
Victor Giurgiu, Director of Thesis
Guiren Wang, Reader

Cheryl L. Addy, Interim Vice Provost and Dean of the Graduate School
DEDICATION

I dedicate this work to my loving parents Gregory and Christina Ennis for always giving the support that I needed for as long as I can remember. As well as Frank Tortorelli, Gregory Ennis Sr., Josephine Tortorelli, and Rosemary Ennis. I am forever grateful for all the long talks, encouragement, and advice whenever I needed it. You have all pushed me to be a better person, Thank You.
I would like to thank and acknowledge Dr. Victor Giurgiutiu for mentoring me during my time at LAMSS. Dr. G has been a great role model as a researcher throughout my time at LAMSS and I wouldn’t have been able conduct this work without his guidance.

I would also like to thank all my other LAMSS Colleagues, William Bobadilla, Siddharth Kannan, and Connor Griffin. Working alongside you all is a memory I will cherish and not soon forget.
ABSTRACT

As in service aircraft begin to age and fatigue, a method for evaluating the operational life they are currently operating under and have remaining comes into question. Structural health monitoring is (SHM) is a popular method of structural analysis with growing interest in the aerospace industry. SHM is capable of damage assessment and structural life estimations.

The ultimate goal of the research presented in this thesis is to develop a methodology of classifying the length of a fatigue crack though the use of machine learning. The thesis has three major chapters as described below.

The first chapter deals with the understanding of acoustic emissions as elastic waves, as well as how their qualities are related to the characteristics of their source mechanism. It is proved that the waveforms of acoustic emissions (AE) signals change as the length of the fatigue crack they originate from changes. It is shown that the AE signals also carry distinct patterns when they originate from a source of crack growth or crack rubbing.

The second chapter of the thesis presents a method of fatigue testing with load parameters determined by the stress intensity factor (SIF) approach. This chapter also explains the setup and results of in-situ fatigue experiments to collect AE signals.

The third chapter of this thesis shows the approach to the implementation of the collected AE data into an AI model. The approach was done with two separate model types, the first being GoogLeNet, a popular convolutional neural network (CNN) model,
and the second being a custom long-short-term memory (LSTM) model. The work goes over the processes taken to process raw data into usable Choi Williams transform (CWT) spectrograms. Model performance enhancement techniques are also discussed in the forms of synthetic data generation and class balancing.

The AI models developed in this paper will have the potential future use of being applied to in service aircraft for the detection of fatigue cracking in order to avoid dangerous failure situations. These AI models can be used with passive PWAS sensors and be used for structural life analysis with minimal monitoring and upkeep.
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LIST OF SYMBOLS

\( \sigma \) Applied Stress
\( \alpha \) Crack Length
\( K_{cr} \) Critical Stress Intensity Factor
\( F \) Loading Frequency
\( R \) Loading Ratio
\( K_{max} \) Maximum Stress Intensity Factor
\( L_{Max} \) Maximum Applied Load
\( K_{min} \) Minimum Stress Intensity Factor
\( L_{Min} \) Minimum Applied Load
\( K \) Stress Intensity Factor
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AE</td>
<td>Acoustic Emission</td>
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<tr>
<td>CNN</td>
<td>Convolutional Neural Network</td>
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<tr>
<td>CWT</td>
<td>Choi Williams Transform</td>
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<tr>
<td>EMIS</td>
<td>Electromagnetic Impedance Spectrum</td>
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<tr>
<td>FEA</td>
<td>Finite Element Analysis</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transformation</td>
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<tr>
<td>HCF</td>
<td>High Cycle Fatigue</td>
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<tr>
<td>LCF</td>
<td>Low Cycle Fatigue</td>
</tr>
<tr>
<td>LSTM</td>
<td>Long Short-Term Memory</td>
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<tr>
<td>ML</td>
<td>Machine Learning</td>
</tr>
<tr>
<td>MTS</td>
<td>Material Testing Systems</td>
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<tr>
<td>NDE</td>
<td>Non-Destructive Evaluation</td>
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<tr>
<td>NRB</td>
<td>Non-Reflective Boundary</td>
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<tr>
<td>PLB</td>
<td>Pencil Lead Break</td>
</tr>
<tr>
<td>PWAS</td>
<td>Piezoelectric Wafer Active Sensor</td>
</tr>
<tr>
<td>SHM</td>
<td>Structural Health Monitoring</td>
</tr>
<tr>
<td>SIF</td>
<td>Stress Intensity Factor</td>
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<tr>
<td>SMOTE</td>
<td>Synthetic Minority Oversampling Technique</td>
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<tr>
<td>TOF</td>
<td>Time of Flight</td>
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CHAPTER 1
INTRODUCTION TO THE USE OF ACOUSTIC EMISSIONS IN STRUCTURAL HEALTH MONITORING

1.1 INTRODUCTION AND STATE OF THE ART

Much of the world’s aircraft has been created using aerospace grade metals, with some dating back decades. Some of these structures are still in active use today, whether it be in commercial flight use, or military purposes. These aircraft have served for a very long period and as a result, their structural health should be closely monitored. As these vessels continue to be used, they must be maintained at a safe level for use. During operation of aircraft and other vehicles, wear and tear can create failure in some of the crucial parts of a structure. An example would be of a panel on a planes wing, the panel would experience turbulence and structural vibrations during service. These stimuli would occur in patterns that could be represented as cycles of loading and unloading. Over time these cyclic loading patterns create fatigue cracking and eventually, total failure.
The field of Structural Health Monitoring (SHM) is the basic study of the “health” of a structure. By being able to determine current health of a structure, as well as diagnose its remaining lifespan, equipment can be operated safer, and repairs/replacements can be made in a timely and controlled fashion. Many different fields take advantage of SHM such as the medical, manufacturing, and aerospace fields. The ability to determine the life of a structure becomes invaluable when viewed from a safety, financial, or mechanical standpoint. SHM can be especially applied to the aerospace industry, as in operation vehicles are constantly being subject to operation conditions which damage and fatigue numerous components of its delicate structure. Within SHM there are two ‘fields’, the active side, which involves sensors attached to specific pieces of a structure in order to gain an understanding of component wear. This method usually utilizes a sensor array and specified tests such as pitch/catch or pulse/echo method for a focused view of a small region. This method is very useful for the detection of damage or defects within a single component. Active SHM must also cause the structure in question to cease any normal operation. The passive side of SHM is the ability to monitor structural health without intrusive testing. Passive SHM usually focuses on performance parameters such as turbulence responses, acoustic wave analysis or vibration analysis and is especially useful since it can be conducted without special attention being given to it. Passive SHM can consist of a one-time sensor bond that allows for the instrumented sensors to ‘listen’ to the structure they are attached to for any signals that could cause concern.[1] The passive approach allows for less time to be spent on any given specific region, but an accurate assessment of a structure’s life can be made. This approach can also be attached in the manufacturing process and stay with the
component during its operational lifespan. Passive SHM can allow for the structure to operate as normal and not require additional testing at normal intervals. By utilizing passive SHM in the design phase of a structure the repair costs and long-term estimates can easily be made. These types of SHM integrated sensors can be applied to aircraft made of aerospace grade metals but may also be applied to composite structures in the future.

Figure 1.1: Diagram of a passive SHM system attached to an airplane.

1.2 ACOUSTIC EMISSIONS

Within material science waves are energy or disturbances that travel across the bounds of the material. They can carry energy far distances along their medium, and if they are collected and analyzed, they can provide information on the source mechanism they stemmed from [1]. Wave propagation in solids has been studied for the last two centuries and has formed much of what is understood of acoustic emissions research. As opposed to what is found in fluids or gasses, acoustic waves travel with different mechanisms in solids, greatly depending on the elastic properties of the carrier solid itself. Metals are a great medium to study elastic waves due to their isotropic and
simplistic nature when compared to materials like composites and rocks. Metals are also best suited for testing involving the study of Acoustic Emissions (AE), since their possible source mechanisms for elastic waves are fewer in number when compared to an anisotropic material like a composite [4]. This is due to the failure of composites becoming complex relations between fiber orientation, fiber volume fraction, and other features, while metals fail in a simpler fashion.

Acoustic emissions are defined as “A phenomenon in which elastic or stress waves are emitted from rapid, localized change of strain energy in material” [20]. These energy releases are caused by elastic properties of the material interacting with a created strain field. These strain fields collapse during a failure event due to the changing geometry of the material and send elastic waves in all directions. It is hypothesized that these strain fields change size in accordance with the amount of energy required for a crack growth event to occur [20], larger cracks have smaller strain fields due to a lower amount of energy required for the crack to propagate. The differences in the energy associated with the AE events allows an insight into the state of material and the defect releasing the energy. These acoustic emissions have been closely studied and researchers have made great advancements in our understanding of them in the last few decades. Many applications of AE research focus on source localization, material performance, and SHM. Within SHM, AE studies have been able to evaluate AE events and determine the location, magnitude, and characteristic of damage in structures. Generally, SHM researchers use acoustic emissions to study the structural health conditions surrounding erosive failure, welding quality, and fatigue failure. The work shown in this thesis focuses on a subset of AE which are generated from fatigue cracking occurring in
aerospace material aluminum 2024-T3. Due to the isotropic nature of the Al 2024-T3 being used, the waves travel with ease through the surface of the thin plates. These waves are bound within the geometry of the thin plates and reverberate off the edges of the specimen itself. This calls for a method of absorbing reflected signals at the central edges of the plate, which could otherwise cause interference with the paths of other elastic waves. By using a material such as a molding clay, generated waves can be absorbed into the clay and dissipate energy which would otherwise be sent back to any bonded sensors and even create standing wave patterns. The clay boundary applied to the specimen is around 25 mm thick on the lateral sides, and 30 mm thick on the longitudinal sides, the thickness at the bottom and top edges also proves useful when attempting to reduce outside noise caused by the fatigue testing machinery itself. The boundary also uses a tapered edge that increases on thickness as the clay moves further outwards towards the edges of the plate. This is to enable even more absorption of elastic waves by the boundary layer.

![AE signal Waveform](image)

**Figure 1.2:** Screenshot from AEwin Software showing a typical AE signal Waveform.

Typical AE signals arrive as a “burst” like waveform with a high frequency, high amplitude section, followed by a lower frequency section concluding the signal. This
waveform is indicative of a sudden failure of material and growth of fatigue cracks. The AE signals are usually isolated from one another, and their rate of appearance is dependent on the stress applied on the testing specimen. These AE events are dependent on the stress applied since they are elastic waves which originate from a region of stress concentration on the tips of a fatigue crack.

Elastic waves are sometime simply modeled in bulk materials where waves are free to travel in any direction as far as they please, however, by studying a thin plate, these wave propagations become more complicated due to the geometrically introduced boundary conditions [4]. This is because the edges of the plate act as a source of reflection that interacts and disrupts waves which travel from the expected sources. These reflections induced by the geometry of the plate can alter the waveforms of all other elastic waves generated by sources on the testing specimen. The imposed boundary conditions are impactful enough that ignoring them or modeling the system as bulk material no longer becomes an option.

1.3 ACOUSTIC EMISSIONS DURING FATIGUE

During the in-situ fatigue experiments, AE signals are analyzed utilizing AEwin software and accompanying hardware. The sensors attached to the specimen are Piezoelectric Wafer Active Sensors (PWAS). The PWAS on the specimen are each soldered to a coaxial cable, which allows for the PWAS to be attached to preamplifiers before being fed into the AEwin computer. These AE contain an extremely small amount of energy when they are generated, they have been compared to “10 orders lower than that of the kinetic energy released from a mosquito landing on a sensor” [23]. As a result,
a set of preamplifiers and highly sensitive data acquisition systems must be used, in this experiment the MISTRAS AE hardware is utilized. This hardware is designed specifically for the extraction of AE data from a set of sensors.

Figure 1.3: Demonstrates the AEwin Software with Channel inputs and Coaxial cables attached to a specimen.

Preamplifiers that are incorporated into the system allow for the weak AE signals to be converted to stronger signals before the AEwin software attempts to register it as an AE event. The preamplifiers are set to produce 40dB amplification of all signals detected by the PWAS. This system also uses a high pass filter which determines when an event occurs and records the event for a set time frame after the event occurs. High pass filters only allow signals which are above a certain threshold to “pass” through into data collection. These preamplifiers can be seen in Figure 1.3.

During these experiments, the AEwin software must be finely tuned to the same settings for all experiments with minor differences in the applied filters. The AEwin software is proficient at collecting any signals collected during testing, however, due to the sensitivity of the PWAS, even a small perturbation on the grip interface could send a
wave that can travel through all four sensors. The AEwin software is also set to conduct experiments while collecting five mega-samples per second, which is enough to give a high-resolution image of all collected signals. The signals are counted as a “hit” when they cross a high pass filter set at around 50dB. This threshold was found after tuning during a fatigue test, it was found that below 50dB was nothing useful. Below was only noise generated by either the grip interfaces, or electrical noise generated by the hydraulics. Depending on the size of the crack, the amount of energy released during AE can decrease, as a result, this filter is reduced slightly as the length of the slit being studied increases. The reduction of the filter is at its height during the 14 mm slit experiments and is tuned to 30dB for outer sensors and 35dB for inner sensors.

While the programs used for processing the files created by AEwin called DTA files being used would remove these noise events from the analysis, the processing of the files in order to do so would take an excessive amount of time, which called for a compromise of the position of the noise threshold. This threshold would be placed just above where the “noise” signals which originate from the grips would start, as AE event are much less likely to generate less energy than noise events. Once the thresholds are set, the AEwin software can be run during fatigue testing to collect signals. These signals that are collected fall into three categories, crack related AE, crack rubbing/clapping AE, and various other sources. The raw data collected from the AEwin program is then transferred to a secondary computer containing a MATLAB script that can analyze the DTA files produced. Each DTA file also has four accompanying text files containing Time of Flight (TOF) and amplitude information, which are used in order to further filter out unwanted data. These tests are the expected order of signal arrival, as well as the
strength of each signal when arriving. The tests are as follows for the TOF and Amplitude data.

TOF: [PWAS 1 & PWAS 2] < [PWAS 3 & PWAS 4]

Amplitude: [PWAS 1 & PWAS 2] > [PWAS 3 & PWAS 4]

These tests used in concurrence with the DTA file allow the script to detect when a signal originates from the expected source. The tests follow the logic that a source originating in the center of the plate would generate a signal that arrives sooner and stronger at inner PWAS. Signals that do not pass these tests are considered noise since they do not occur in the area being studied. These tests were verified by a simple experiment involving an active pristine coupon. This coupon was created with the same PWAS bonding and geometric placement as the other samples. However, this coupon was put under a fatigue test without a defect at its geometric center as seen in Figure 1.4. The idea is that if there are any signals collected by the AEwin software, they would not be AE related since there was no initiation hole or notch at which a fatigue crack could form. Since there is no geometry for stress to accumulate and cause wear on the surrounding material.
Figure 1.4: Graphic showing PWAS layout on a pristine aluminum sheet

During the experiment the signals were collected as usual, and it was found that no signals collected passed the TOF and amplitude screening. However, there were over 4000 unique signals collected, all of them failed the AE filtering tests and are attributed to either the grips, or electrical humming of machinery. This testing verified our previous methods of locating AE sources via simple TOF and amplitude analysis coupled with the geometric placement of PWAS. Since there were no events captured which pass the TOF and amplitude tests, it can be concluded that there were no signals originating from the plate, and that signals collected during other tests must be originating from the intended AE source.

During fatigue testing, AE activity during the test changes according to the stage of tensile testing of the material. During the total span of the test, it is found that the amount of AE collected is at maximum during the initial stage of the test, before yielding begins to occur, and slows down once failure takes place. AE events also occur when the stress is changing at high rates and tends to be less frequent during static loads. This can be seen in Figure 1.5.
AE signals generated during fatigue testing can be traced back to many different source mechanisms such as crack initiation, crack growth, crack rubbing. It has been agreed upon that as the crack growth rate increases, the AE count rate also increases [3], however, the rate at which each possible AE source increases is not proportional. For example, AE rate for crack rubbing does increase as the crack grows due to the creation of additional possible rubbing surfaces, these rubbing surfaces have an “active region” where the rubbing is occurring most heavily due to the deformation of the crack profile according to the total length of the crack, as the crack grows outwards, the active region shifts towards the direction of crack growth and with enough growth, the central region of the crack profile plastically deforms and emits fewer AE due to crack rubbing. These crack growth source typically changes according to the three-stage model proposed by Paris-Erdogan, where the source is somewhat quite in Stage I, II, but explodes in an exponential fashion during Stage III. This explosive crack growth creates a region where the total sum of AE for a given crack length is lower than that of larger lengths. This is exemplified by [3] in Figure 1.6.
1.4 METHOD OF AE SIGNAL GENERATION AND CAPTURE

The chosen method of AE generation in this experiment is Low Cycle Fatigue (LCF) experiments, LCF experiments are tests where there is a cyclic application of high tensile stress and low frequency. This test is conducted as an LCF test as opposed to a High Cycle Fatigue (HCF) test because the amount of time required to run each tests decreases dramatically, while an HCF experiment calls for hundreds of thousands to millions of cycles, spanning hours to days length. An LCF test can be conducted fully in the span of a couple of hours and only uses tens of thousands of cycles. During LCF tests, fatigue cracks grow in the direction perpendicular to the direction of applied tensile force. Fatigue tests have proven useful when trying to closely resemble the wear and tear of in-service machinery and materials. These fatigue tests are operated by the use of an MTS-810 system with hydraulic wedge grips. These machines can apply a consistent cyclic loading over a predetermined load level and duration. A testing specimen can be placed within the grips and the MTS machine is given instructions as to how long the load
levels, and cycle count. The setup also contains an easy-to-use software which runs the MTS-810.

In the last couple of decades sensors used in SHM have improved dramatically, some of the most popular now consist of piezoelectric materials which couple to a surface and minimally intrude on the material being studied. The sensors chosen in this experiment are piezoelectric wafer active sensors (PWAS). These sensors are small 7 mm diameter and 0.5 mm thick piezoceramic disks. PWAS are inexpensive and easy to couple to the testing specimens. Due to their small size and weight, as well as the ease of application to structures PWAS are a great selection for the collection of AE signals. The PWAS themselves are very efficient are receiving the elastic waves produced by an AE source and turning them into an electric signal. These PWAS take advantage of the piezoelectric effect, which is the generation of mechanical strain when electricity is applied, and the reverse holds true as well [2]. The PWAS respond to the waves produced by AE events and release a proportional electric signal. These PWAS act by “pinching” the surface they are coupled to as the elastic waves passes through, this can be seen in Figure 1.7.[1]
1.5 DISCUSSION OF AE SOURCE MECHANISMS

AE events can be the product of multiple different source mechanisms during a fatigue test, some of these sources include crack advancement, crack rubbing, and crack clapping. According to the source mechanism that releases an acoustic emission, the structure and typical characteristics of the AE waveform vary. And it becomes important to be able to determine the source mechanism based on the waveform collected at the PWAS. Type 1 signals seen in Figure 1.8 indicate a crack growth event.

Figure 1.8: Shows an experimentally collected Type 1 AE, signifying a crack growth event.
This shape was also confirmed by the work of Dr. Hanfei Mei [2] in Finite Element Analysis (FEA) in Figure 1.9. The Type 1 wave was modeled as Mode 1 failure where the crack tips were pulled in opposite directions.

Figure 1.9: Crack Advancement simulations in FEA

The Type 2 signals seen in Figure 1.10 indicate a crack rubbing/fretting event. These events occur in the unloading portion of the loading cycle and caused by the rubbing edges of the crack face as the tension is released and elastic deformation is reduced. The Type 2 signals contain information about the crack present but are a byproduct of growth.

Figure 1.10: A screenshot depicting an experimentally collected Type 2 AE signal, signifying a crack rubbing/clapping event.
These signals were modeled as a shearing event at the tips of the crack in Figure 1.11. The geometry-imposed boundary conditions make the system difficult to interpret numerically and becomes a perfect candidate for FEA simulation. By simulating an AE event within an FEA simulation, the expected waveform can be determined at any given point on the thin plate. The different types of source mechanisms can also be roughly modeled by the type of excitation used in the model [2].

**Figure 1.11: Out of plane rubbing Simulations in FEA**

The simulations ran showed the differences in waveform for the crack advancement and out of plane rubbing modes. The simulation waveforms patterns have a close correlation to what is seen in the experimentally collected signals. This verifies that the PWAS are able to collect quality AE events during the in-situ fatigue.

It was found that these AE signals also change their frequency peaks in accordance with the size of the crack present. This shift in frequencies has been modeled in finite element analysis as well as confirmed experimentally by [2]. These frequency shifts are also visible when comparing a handful of signals from the same crack length. Several type 2 signals that were all collected in the 10-11 mm range are shown in Figure...
1.12. They all show a similar peak placement pattern. The waveforms present are also characteristic of a Type 2 signal as shown in Figure 1.10.

Figure 1.12: A screenshot depicting 10 overlayed Type 2 signals in the time and frequency domains.

Both types of signals have been shown to hold information about crack length within them. As a result, both are included in the labeled machine learning dataset. The labeling process for these signals was very precise in order to give the limited data available the most information. The timestamps for each AE hit recorded were collected by the AEwin software and compared with the estimated crack growth rate and visual checks of length, the estimated growth rate was then used with the amount of time elapsed during the experiment to determine the length of the crack at the time of the signal.
Figure 1.13: 10 mm hit in the time and frequency domain with labeled peaks.

The apparent peak frequencies for a 10 mm crack source in Figure 1.13 are found at 94, 117, and 370 kHz. These peaks are located nearby the peaks found in FEA; however, they are not at the exact locations. These differences can be attributed to the non-perfect PWAS symmetry, as well as other conditions regarding the coupled system.

Figure 1.14: 12 mm hit in the time and frequency domain with labeled peaks.
Figure 1.15: 14 mm AE Hit in the time and frequency domain with labeled peaks.

The same observation holds for the 12 mm signals seen in Figure 1.14, the peaks here are all shifted over to higher frequency peaks. The 14 mm response seen in Figure 1.15 had peaks found at 96, 343, and 461 kHz. Yet again, the peaks here are similar, but not exact to the FEA peaks.
During testing, there were three separate types of plates, each representing a 2 mm increment of growth, 10-12 mm, 12-14 mm, and 14-16 mm. The typically found pattern for each of the testing samples can be seen in Figure 1.13, Figure 1.14, and Figure 1.15. In comparison to the FEA modeling completed by Dr. Hanfei Mei, there are correlations between the peak locations, however, a portion of these peaks are shifted and occasionally missing. These discrepancies are attributed to the differences between the testing and simulation environment, there are variables which cannot be determined in FEA that are present within the experimental setup. However, these shifts in frequency peaks are consistent across each of the experiments, which allows for the signals to be compared. In concurrence with theory there are apparent shifts in the frequency peaks, which are associated with the growth of the crack. It is an interesting observation that the number of frequency peaks seem to become more numerous as the crack length grows in
size, which is also in agreement with theory. The low frequency region also appears to become much more complex as the crack size changes.

1.6 SUMMARY AND CONCLUSIONS FOR CHAPTER 1

In summary, the basis that the proposed experimentation wishes to test is laid out. The predicted AE events are to be generated with the help of in-situ fatigue experimentation and will revolve around the complex structures of acoustic emissions and their relation the characteristics of the source mechanism emitting them. The source mechanisms for crack rubbing and advancement have been identified through simulation and experimentally verified. As well as the approximate peak frequencies and mode shapes that are expected for the proposed crack lengths.
CHAPTER 2

THE USE OF LOW CYCLE FATIGUE EXPERIMENTS TO PRODUCE

AE SIGNALS

2.1 INTRODUCTION AND STATE OF THE ART

In the field of Structural Health Monitoring, the study of fracture mechanics is extremely relevant. Fracture mechanics is the study and understanding of different modes of failure and how they can occur/interact with a structure. There are three failure modes studied in this experiment, Mode 1 is the normal opening mode. This mode is active when there is an application of force which is normal to the crack direction. Mode 2 and Mode 3 are shear and sliding modes as shown in Figure 2.1. Mode 2 and 3 are present during the crack closing process and generate acoustic emissions in a rhythmic fashion.

Figure 2.1: Diagram of the three modes of failure

For the purposes of testing, Mode 1 failure will be studied more heavily since it is closely related to the growth of a fatigue crack. This type of failure mode is highly
prevalent and occurs commonly in most aircraft and watercraft. This type of failure can induce fatigue cracks, which can rapidly grow and cause total failure of a component. These growing cracks are a telltale sign of the beginning of the end for a structure, and by being able to understand the growth of these cracks, structural health can be accurately determined.

Fatigue testing is a form of destructive testing which is used to determine the fatigue life of a material. It has been a widely used method for the last few decades, and its goal is to simulate real operating environments for a material or specimen. Some of the main variables considered are Loading Ratio R, Loading Frequency F, Loading Range, and amplitude variance. Loading ratio is the ratio between the maximum and minimum load used. Load ratio has been found to determine the rate at which AE signals appear, beyond that of the first cycles. As the Load Ratio R increased, so did the AE count rate as seen in Figure 2.2[15].

![Figure 2.2: Shows a graph plotting AE count rate vs R value vs Crack Length [15]](image)
Loading Frequency $F$ is the rate at which loading is applied, loads are typically applied in a smooth sinusoidal fashion, with the frequency of the sinusoid being the loading frequency. Amplitude variance is another of the important variables to consider for fatigue testing, typically, loading in the real world is not a constant amplitude, and tends to have different maximum and minimum loads over time. Fatigue experiments conducted for the purpose of AE collection is conducted using a modified version of variable amplitude fatigue loading. Since the amplitude of the load will change as the load increases, but the frequency and load ratio will remain the same.

![Variable Amplitude Loading Curve](image)

Figure 2.3: Displays an image of a Variable Amplitude loading curve.[16]

During these fatigue tests, materials are loaded with tension and cycled between two specified loads. Often an artificial defect is created in the center of the plate, such as an initiation hole, side notch, or slit which allows for a region of stress concentration to form around the defect’s geometric boundaries. When the loading is conducted, these defects will spawn fatigue cracks due to the generated local strain fields. Fatigue cracks will become the result of high stress concentrations at critical regions surrounding the defect, and they will continue to grow as stress continues to accumulate at its tips. As the cracks grow, they typically follow an exponential growth pattern and quickly lead to...
material failure. Each time the crack propagates in the direction of growth, it is considered a “growth event”.

2.2 STRESS INTENSITY FACTOR CONTROLLED CRACK GROWTH

In the field of SHM, there are many ways to approximate stress and strain fields at complex geometries, within this study, the Stress Intensity Factor (SIF) approach will be utilized. Stress intensity factor $K$ has the formula.

$$K(\sigma, \alpha) = C\sigma\sqrt{\pi\alpha}$$

where $\alpha$ is the crack length $\sigma$ is the stress applied, and C is an experimental constant that varies based on the geometry of the material and load applied. This method allows for a simple approach to the stresses at the complex crack tips. There also exists a critical point $K_c$ which denotes the critical stress intensity factor, a value that is a material property that dictates when the material will experience failure. According to this formula, the stress intensity factor is a function of both crack length and stress applied.

This is important since the function becomes exponential if the crack length $\alpha$ increases through a fatigue experiment. If only $\alpha$ is changing throughout the experiment, then a means to controlling the crack growth rate would be by adjusting the applied stress $\sigma$.

This is further explored by Dr. Victor Giurgiutiu [1] during discussion on component life prediction. Where a typically observed crack growth behavior is that of exponential damage accumulation. This method shows a critical crack length and failure point that occurs once accumulation becomes uncontrolled. This model can be applied to real world applications where loading cycles represents in operation conditions, such as
turbulence landings, or takeoffs. Due to the exponential nature of crack growth, when they are small, they grow at a very slow pace, and as they grow, they become highly unstable and create dangerous scenarios. This lends to the idea that the identification of cracks as they are still small and crack growth rate is low is paramount to ensuring structural safety.

Parris and Erdogan [6] worked with the Stress intensity factor $K$ to model a single fatigue cycle, where the crack is subjected to a range of stresses set forward by the prescribed loading cycle. It was found that the crack growth rate depended on the ratio of stress intensity factor experienced in a single cycle, $K_{\text{min}}$ and $K_{\text{max}}$. This relationship is a function of $\text{SIF}$, and the growth rate of a fatigue crack, which shows a three-section understanding of crack propagation, a first growth section where the crack begins to grow slowly as a quasi-logarithmic function, a secondary section where the crack grows at an almost linear rate, and a third section where the cracks show an exponential takeoff of crack length, which ultimately leads to total failure. This curve is a result of a power function set forth by Parris-Erdogan and holds for short fatigue cracks.
Figure 2.4: Crack growth Log chart showing crack growth vs stress intensity factor [6]

SIF is a value that corresponds to the accumulation of energy at the crack tips. By using a constant plate width, constant applied load, and growing crack length, the growth of the crack is found to be exponential in rate. However, by changing the load applied in accordance with the crack length, growth rate of the crack can become a quasi-linear function.

Figure 2.5: Shows a typical crack length vs cycles diagram in blue, and the intended results of SIF controlled loading in red.
This can be observed in the work done by Dr. Roshan Joseph in his experiments involving High Cycle Fatigue (HCF) [9]. The growth found in his experiments showed a more linear pattern of growth as opposed to an HCF experiment with a constant load. The load that determines the SIF calculation is the mean load of the cycle pattern. Typically, this value is selected based on the intended growth rate of the experiment, higher SIFs have shown higher rates of growth. With the previously used SIF of 237.5 MPa m$^{-1/2}$ giving a growth rate of 0.1mm /Kcycle. In a preliminary experiment, a crack was grown from a 1 mm initiation hole located at the geometric center of an aluminum coupon.

The crack was fatigued until it was roughly 11 mm in length, then the steady crack growth loading patterns were implemented. The crack was grown from this point and carefully observed every 200 cycles, as the crack grew, the load applied was changed in accordance with the formula for SIF in order to keep a constant value at 237.5 MPa m$^{-1/2}$. The crack was shown to hold a steady rate of growth as well as produce satisfactory AE signals.

![Crack Length(mm) Vs. Cycles](image)

Figure 2.6: Experimental results of SIF controlled crack growth experiment
This test shown in Figure 2.6 show a relatively linear crack growth signified by an R\(^2\) value of 0.90, meaning that the function that could model this growth is almost purely linear. The crack experienced a growth rate of \(~0.1\ \text{mm/Kcycle}\). This rate held steadily throughout the experiment.

2.3 MANUFACTURING AND IMPORTANCE OF A “HAIR THIN SLIT”

![Diagram](image)

Figure 2.7: Sketch of a Hair-Thin Slit specimen as well as its specifications and loading parameters.

The testing specimen that is manufactured is a 1 mm x 103 mm x 300 mm piece of Al 2024-T3. It was created using the equipment at the UofSC machine shop, which included a shear cutter and various sanding tools. This specimen is designed to fit neatly within the MTS-810 4-inch grips and give enough space for a clay NRB, four PWAS sensors, and the hair thin slit.
During fatigue of the test specimen, fatigue cracks both open and close during cyclic loading, these interfacing surfaces create signals during closing. These signals become overwhelming in number when compared to growth AE events, and as a result a method to reduce the amount of AE generated from rubbing/clapping was created. By using a hair-thin slit of 0.15 mm width, a crack could be approximated without any significant rubbing surfaces. By removing the otherwise interlocking surfaces of a fatigue crack, a crack with dominant amount of type 1 signals can be created. These slits are only grown by 1 mm on either side to maintain a very low amount of rubbing/clapping surfaces along the crack profile. This slit would be approximated as a simple crack. Many methods of creating a 0.15 mm slit were expensive and required a waterjet cutter, or laser equipment. A cheaper yet equally accurate method of generating hair thin slits would be created in house in order to avoid these costs. This is accomplished by using a 0.15 mm
thin Dremel disk tool and slowly cutting along the geometric center of the test plate. The Dremel disk tool is attached to a drill press and a jig is created to keep the plates aligned during creation. Due to the circular shape of the disks, there is a semi-parabolic shape left at either tip of the slit, to remedy this, a small amount of diamond coated floss is used to remove the excess material.

Figure 2.9: Shows the setup of a Dremel Disk tool designed to cut thin slits in aluminum.

This method allows for the quick and accurate creation of over a dozen hair thin slits at various lengths. The resulting slit was widened to required length and flossed at either end to ensure a straight edge. These slits were created at lengths of (10,12,14) mm and were each grown by 2 mm in total. The slits grew at the expected rate of growth for a naturally grown fatigue crack of the same length. This allows for a slow, controlled environment as well as an accurate measurement of total growth and labeling of each AE hit collected during experimentation. This range of slit length between 10-14 mm was also chosen due to the geometric limitations of the Dremel disk tool, as a 10 mm slit was the smallest possible slit length the Dremel could cleanly cut. It would be preferable to
work with smaller fatigue cracks as opposed to larger since they fatigue cracks should be discovered as soon as possible, and AE generated from smaller cracks have higher frequency components, which is difficult to collect with the currently available sensors.

2.4 LOW CYCLE FATIGUE EXPERIMENTAL SETUP

Fatigue testing is an easily reproducible experiment and is operated with the use of a custom machine, which cycles loads and counts cycles for the user, the range at which the machine applies load is quite consistent. Therefore, the parts of the experiment that need to be scrutinized the most are the applied sensors, as well as the incremental crack growth value collection. The setup for the Low Cycle Fatigue (LCF) experiments begins with a check on the sensing equipment that will be utilized. Sensor integrity during the fatigue experiments is ensured by a couple of methods, the first of which is by measuring the capacitance of the free unbonded PWAS, this allows us to find four PWAS with similar electrical structures. Capacitance of a sensor is equivalent to the amount of charge that can be stored in its electrical structure, this value can change as the sensor has its leads clipped or extended via soldering. In order to measure capacitance of PWAS (STEMINC SM412, 7 mm diameter and 0.5 mm thick) by utilizing a multimeter. PWAS are then grouped with similar capacitance (±.03nF), the typical capacitance of PWAS is ~1.35 nF.
Figure 2.10: Shows five free 7 mm wide PWAS.

This process is repeated until six similar PWAS are found. The sensors are also attached to coaxial cables which are soldered to the ends of the red and black leads that the PWAS come with from the manufacturer.

PWAS are bonded to the test surface by first preparing the surface, sandpaper is applied in order to create a rougher surface for the PWAS to bond to, this is followed with the application of a weak acid, followed by a weak base, in order to remove any surface contaminants present. The surface is tested for contaminants with a sterile cotton swab, and the process is repeated until no residue is picked up on the swab. Once the surface is prepared the AE-15 resin and epoxy mixture is created and drop roughly 0.25 mm in diameter is placed onto each the PWAS. The PWAS and adhesive are then cured as according to the curing cycles provided by the manufacturer. The surface preparation for bonding is of high importance and insures an adequate amount of signal collection across the frequency spectrum for the expected AE signals.

The placement of sensors was chosen to be in a straight line along the horizontal center, and 5 or 25 mm away from the vertical center. This grid allows for a near and far
field assessment of AE signals released from the center of the plate. This setup also allows for the use of PWAS 3 and PWAS 4 for signal collection due to symmetry. The collection of signals originating from PWAS 3 and PWAS 4 will be of the same characteristic shape and contain similar time and amplitude information. While PWAS 1 and PWAS 2 will contain a different set of similar data.

![Image showing PWAS placement and distances](image.jpg)

Figure 2.11: An image depicting the correct placement of PWAS and their respective distances, it also shows the numbering method.

During the in-situ experiment there are methods employed to determine sensor integrity and allow for troubleshooting the AEwin software. One of the common issues the sensors can experience is a weak bond or debonding during experimentation, by not having a strong connection the specimen, the PWAS oscillate much more violently since they are only partially coupled to the test plate and can trigger the AEwin software or introduce large levels of signal distortion to the AE hits, or not be able to pick up high frequency components. A useful method of testing these PWAS is by conducting a Pencil Lead Break (PLB) test which can be seen in Figure 2.12.
These PLBs are well documented as a good source of AE simulations, and are extremely accessible and easy to conduct, they can even be conducted during experimentation. The pencil lead being pressed down deforms the plate, and as the lead snaps, the released stress creates an elastic wave, similar to that seen during an AE event [19]. This type of test and the signals produced are extremely reproducible if conducted properly. There are many variations of PLB signals in literature due to the different variables including lead length at break, angle at break, lead diameter, and other handling styles. Within the PLB tests conducted in-situ, 0.5 mm lead was always used, as well as about 4 mm of lead at the time of break, and a 30-degree angle at break.
Figure 2.13: Demonstrates the correct placement of a mechanical pencil at tip of a hair thin slit.

The source was placed at one of the tips of the slit in order to be able to conduct a comparison of collected signals using the symmetry of the plate. The sensors pick up the waves emitted from the lead breaking and a simple comparison of waveforms, amplitudes, and TOF can be used to make conclusions on the bond quality present at each PWAS.

Figure 2.14: A Rigid wood block support is being used with correct placement before a PLB is conducted.

These PLB tests should be done at the end of the bonding/soldering process as well as intermittently during fatigue testing. This ensures that the sensors have not been
damaged and the signals being received are crisp. The experimental setup is shown in the above figure.

In order to gain the highest quality signals, it is essential that the wooden block support is utilized while conducting initial PLB testing, signals have much less noise when using this method and it will help identify any possible patterns to look out for. In the unsupported PLB tests, the flexural waves generated by the pressing of the pencil warp the signals being studied and can hide important characteristic of the collected waveform. These dampened signals are also easier to evaluate and the peaks and jaggedness of curves, a successful PLB test will show all four sensors having similar peaks, logical amplitudes, and similar reflections.

While using the MTS machine, it is advised that a high load setting is applied before PLB testing, doing this also reduces the amount of noise present when conducting the PLB test. This is due to the tensile stress present in the plate, reducing the amount of bending possible in the out of plane direction. [19] Creating a more rigid plate for the pencil to press into. There is a comparison shown in Figure 2.15, Figure 2.16, and Figure 12.17.
Figure 2.15: An unsupported PLB test showing the intense vibrations collected during testing.

In the unsupported PLB test, the specimen was simply laid down on a wooden table and supported by its own NRB, the specimen experienced vibrations beyond what the experiment is supposed to yield. The NRB supports the outer edges of the plate and allows for the bending of the plate accompanying the pencil lead being pushed into it.

Figure 2.16: A wood block supported PLB test has fewer initial vibrations, and the waveforms now contain a characteristic shape.
A simple block of wood was placed on the inner surface of the specimen on the opposite side of the sensor array. The wooden support was able to dampen out any flexural waves created by the pressing of the pencil. The waveform seen here is much easier to analyze visually.

![Waveform images](image)

Figure 2.17: A PLB test under 4000 lbf loading shows the same effect as the wood block supported PLB

Another method employed to ensure PWAS similarity and integrity is testing the Electromagnetic Impedance Spectrum (EMIS). This EMIS testing is done with the use of a BODE-100 analyzer as seen in Figure 2.18
These tests evaluate the PWAS response to being activated within a prescribed frequency range, for the purposes of this test, it will be conducted between 0 and 1000kHz. This test measures the vibrations of the PWAS as it is activated, allowing for an insight into the resonance peaks patterns. Testing should be done at every critical step of the specimen creation and experimentation. The EMIS testing assures that the bond quality has not deteriorated at any step of the experiment and also determines whether or not the PWAS is correctly receiving data across the entire frequency spectrum. These tests are done continuously throughout the experiment, starting with an initial comparison of prospective PWAS. These PWAS must have similar peak locations and amplitudes. This ensures none of the PWAS are initially damaged and that there vibrating at the expected resonant frequencies.
The initial EMIS test for each PWAS is conducted with a free hanging PWAS. This test gives each PWAS a benchmark vibrational frequency and can be referred to further down the bonding process. It can be seen in Figure 2.19 that the unaltered natural frequency peaks of an unbonded PWAS are at ~370 kHz as well as ~780 kHz. These peaks are important to locate as throughout the process they will shift with the mechanical coupling to the system. Although the fact that there are two peaks, a larger peak at lower frequency, and a secondary peak at higher frequency is present through bonding is an important benchmark for the sensor integrity.
There is a notable shift in frequency peaks once the PWAS have been bonded to the aluminum coupon in Figure 2.20. It can be seen that the peaks shift in a familiar fashion across all four PWAS which were bonded. This indicates a successful bond of all sensors and allows for a higher trust of received signals. These peak shifts are due to the mechanical coupling of the PWAS to the testing plate, which causes the system to have a different natural resonance peak. There is also a notable amount of noise attached to each signal. This noise is due to the vibrations present during the conducting of the tests, these oscillations will dampen out as the specimen creation process continues.
Figure 2.21: EMIS readings for four PWAS after installing the specimen in MTS grips.

The EMIS readings conducted while the plate is loaded show very little vibration, this is due to the tension applied reducing any flexural vibrations caused by the activation of the PWAS. These EMIS readings are the cleanest when compared with the other testing environments and are what are closely studied.

Figure 2.22: Graph that shows the EMIS readings for a test where a PWAS became disconnected from the coaxial cables.

It is important to note that during these tests one of the PWAS was consistently different than the rest, it showed a much higher initial frequency peak. This is indicative
of a weakly bonded PWAS due to its greater ability to vibrate after bonding. The mass of
the plate isn’t being fully utilized in damping the PWAS vibration and allows for a higher
amplitude frequency peak. This PWAS eventually experienced a short in the wire leads
and the resulting EMIS is seen in the above figure. Therefore, after the PWAS are bonded
to the plate, it is recommended to check the reading for any PWAS that have noticeable
differences than the rest, as they may become damaged.

EMIS spectrums for an ideal bond are seen below in Figure 2.23, in this figure all
peaks have both a similar location, and amplitude. It is imperative to achieve an EMIS
reading like this in order to proceed with testing.

Figure 2.23: Graph that shows the EMIS readings for an
ideal EMIS test.

During SIF controlled fatigue testing, an exact account of the crack length at the
beginning and end of each test must be known in order to accurately account for crack
length changes. In order to achieve this, Eddy Current testing is employed. It is widely
used within SHM due to its noninvasive analysis of internal features of materials. Eddy
Current testing is a popular method of Non-Destructive Evaluation (NDE) which can
detect discontinuities in a metallic material by measuring the eddies created when a magnetic field is presented. This method also is highly useful since it can be done with the use of a handheld probe, capable of being run across the testing specimens. Eddy Current testing is very delicate and proper setup is very important to its usage. In Figure 2.24 below, two Eddy Current scans can be seen, one of which is an untuned Eddy Current test, and one has been finely tuned. It can be seen that the poorly tuned test approximated a crack that was around 2 mm longer than the actual crack present. Tuning is done by an input of the magnetic properties of the aluminum alloy and consideration of the specimen geometries such as scanning width, and thickness.

Figure 2.24: Shows a comparison of a tuned Eddy Current test (upper right), and an untuned Eddy Current test(left) as well as an image of the crack being examined.

Another method used for crack length estimation during testing is by using a microscope and measuring tape. This method is used alongside a thin coat of polish which removes surface blemishes. Since two methods are being used to approximate crack length during testing, a confirmation of each is conducted by the other.
Specifications for this fatigue test are a loading frequency of 4 Hz and an R value of 0.1. These specifications were determined to be the most efficient and yielded the lowest noise when compared to other loading frequencies and R values. The data collection process was very controlled as to ensure labeling of data was as precise as possible. Around every 500 cycles, a visual check of the crack length, as well as an Eddy Current scan of the crack was conducted in order to make any load adjustments needed to keep a constant SIF.

Figure 2.26: Screenshot of the loading curves provided by the MTS-810 software; image shows a smooth sinusoidal pattern.
In order to ensure accurate loading curves, a small piece of equipment was attached to the MTS-810 load cell to monitor its output. This machinery saved and displayed loading curves generated by the MTS machine as seen in Figure 2.26. The MTS-810 consistently put out symmetric, constant loading cycles between the prescribed ranges. This gave confidence in the SIF controlled technique as well as accurate determination of when crack growth events would occur.

The experiment is conducted by first gathering the necessary materials needed to operate the MTS-810, AEwin software/hardware, as well as the test specimen with soldered coaxial cables. The MTS-810 is first calibrated with the use of a “dummy” plate, which allows for the MTS machine to begin loading within an acceptable tolerance. The range for which the dummy plate is loaded is between 60-100 lbf for 5 cycles. Once the cycles are completed, the dummy is removed from the hydraulic grips, and the test specimen is loaded in its place. The grips themselves cover the entire 100 mm width of the plate and come 50 mm inwards on either end.
Figure 2.27: Picture shows the experimental setup containing the MTS hardware, software, and AEwin computer.

These grips are capable of an even grip across the gripping surfaces in order to ensure a uniform stress field across the plate. A preliminary PLB test, as well as an EMIS collection for all PWAS is conducted to ensure no damage was accrued during the transportation of the test specimen. If the PLB and EMIS show results congruent to what was collected before transport, the first batch of cycles is conducted, the loading is determined based on the type of specimen being used, as well as its current state. The load is applied at a rate of 100lbf/s and must first ramp up to a value equal to \(\left(\frac{L_{\text{Max}}+L_{\text{Min}}}{2}\right)\). Once the load is applied, the MTS-810 begins cycling between the Max and Min loads at a rate of 4 Hz for around 500 cycles. Once the cycles are finished, the specimen is inspected both visually and with the Eddy Current probe, load is adjusted according to the growth of any cracks present, and another 500 cycles are run. Visual inspection of loading is done with the use of a microscope and sticker with mm
increments on it, the crack tips are viewed with the microscope and any cracks are compared with the mm labels on the sticker. This is done for both sides of the plate, and both ends of the crack. This can be seen in Figure 2.28.

![Image](image_url)

Figure 2.28: Image that shows a crack at either side of a 1 mm initiation hole as well as the mm increment sticker.

The load adjustment was changed for every mm of growth. This process of loading and adjustment continues until a total crack growth of 2 mm is present. Once the desired crack length is reached, the specimen is unloaded at a rate of 100 lbf/s and removed from the MTS-810.
2.5 LOW CYCLE FATIGUE EXPERIMENT RESULTS

Figure 2.29: Graph showing the Crack length vs Cycles.

This fatigue experiment process was repeated for each specimen type and the results were plotted on Figure 2.29. As seen in the figure, all three types had a growth rate that could be fit to a linear function with an $R^2$ value of at least 0.89. The growth rates experienced for each plate were 0.3 mm/Kcycle for the 14-16 mm specimen, 0.9 mm/Kcycle for the 12-14 mm specimen, and 0.2 mm/Kcycle for the 10-12 mm specimen. The growth rates align with the respective SIF values used for each experiment. The SIF used with the 10-12 mm was plate was 161.5 MPa m$^{-1/2}$, the 12-14 mm specimen used a value of 400 MPa m$^{-1/2}$, and the 14-16 mm plate used a value of 237.5MPa m$^{-1/2}$. These SIF values were shown to be directly correlated to the rate of growth experienced at each specimen.
Figure 2.30: Shows crack tips forming at ends of a 10 mm slit.

The testing concluded for each specimen type after there was 2 mm of cumulative growth on either side of the slit. Once the growth was completed for all experiments, there were a total of 216 10-12mm AE hits, 224 12-14mm AE hits, and 198 14-16 mm AE hits. There was a total of six tests ran equally spread out among the 3 possible plate types (10,12,14) mm slits. The data is saved as .DTA files within the AEwin software and easily exported to MATLAB. These files would give the time domain responses of all recorded events for each test. It took ~3 specimen per type to gather ~200 AE signals for each crack length.
Figure 2.31: Depicts a screenshot of the AEwin software hit plot, with views and zoomed in areas of select hits.

During the fatigue testing, there are many types of signals which appear as “hits” but are disregarded as outside interference. These signals are very common and create a necessity for additional filtering, a small fraction of the total amount of AE “hits” are authentic AE events from crack related activity. Although, throughout the test it is important to check for AE “like” hits to ensure that the sensors are gathering valuable info along with the noise.

2.6 SUMMARY AND CONCLUSIONS FOR CHAPTER 2

In summary, the procedure and instrumentation needed for the in-situ fatigue experiments has been discussed. The in-situ experiments are conducted in the form of SIF controlled fatigue experiments, where the testing specimen consists of an aluminum 2024
T3 coupon with a 0.15 mm slit at its geometric center. These tests are run for each slit length and data is collected using the MISTRAS AE system.

The initial SIF controlled growth experiment showed that the crack growth rates were being slowed down and more controlled by load adjustments. Which allowed for a more accurate reading of crack length to be taken at each stoppage point during the fatigue test. These labels of crack growth that are more precise will assist greatly during the data analysis stages of the AI approach.

The AE collection processes showed that the PWAS were picking up many different signal sources and the applied filters allowed for a large data pool of signals in which the quality AE signals could be derived from. The AE data collected was shown to be a sufficient amount for the application into a machine learning model.
CHAPTER 3
ARTIFICIAL INTELLIGENCE APPROACH TO THE DETECTION OF
CRACK LENGTH

3.1 INTRODUCTION AND STATE OF THE ART

With recent advances in the quality and availability of sensing equipment and computing power, the collection and analysis of high-quality data has never been easier. One of the extremely potent methods of data analysis is by utilizing machine learning algorithms. These algorithms are capable of “learning” highly complex patterns within data and are capable of doing so in a very short time. These models become akin to experts in a specific type of data and can be utilized at any time with a computer. These models have shown that they are capable of even outperforming humans in data processing and pattern recognition. Since SHM is such a data driven field, and there are a multitude of signal types generated from various sources, machine learning becomes an ideal way to perform SHM within a given system. These models could be attached to passive sensor networks and constantly be detecting any signals that could be cause for concern.
The running of AE generating experiments has some limitations to its amount of reproducibility, these experiments have many variables which control the signals produced. Even if a perfect reconstruction of a test is conducted, down to the specimen geometries, load settings, and amount of crack growth. The exact same signals will never be received. These variations in testing results call for a method of signal analysis and interpretation that is not perturbed by these differences in data. Machine Learning (ML) presents itself as a method which can overcome these differences that cannot easily be parsed by the human mind. Deep Learning ML models are a branch of model that is built following the basis set in biology, these models are arranged in layers and nodes which pass information between one another, much like what is seen within brains found in nature.

Figure 3.1: Shows a typical deep learning ML model. [14]
Acoustic emissions have been studied through the lens of machine learning before by [9] in a study where acoustic emissions data was collected and labeled as either, crack related or noise. The model was able to accurately distinguish between what was and wasn’t crack related with a high accuracy of 95%. This is a great starting point for the use of ML within SHM since it would allow a sensor to determine when a crack growth event is occurring, but lacks the information related to the size of the crack and predictions as to the state of the structural health. The addition of a discretized crack length classes within a ML model would be able to help assess the structural health of a component by estimating how large of a fatigue crack is present in the structure. A model would be able to distinguish between a smaller, less urgent crack and a larger crack which would be much more urgent and could indicate a short amount of “life” left in the component. Within this research, a classifier model will be used to determine the length of the crack acting as the AE source. This ability to determine the length of an AE generating crack can be crucial to the determination of the structural health of a component. These ML models can easily be transferred onto an on-board computer which would be able to diagnose health and fatigue cracks present in real time. This technology would be a constant watchful eye for any possible material fatigue, which would not otherwise be possible, especially during flight.

3.2 DATA FILTERING/PREPROCESSING METHODS EMPLOYED

The initial time domain signals are collected with a span of 150 microseconds and are triggered by an initial high pass filter. These time domain signals are useful in determining the type of AE source they originate from, but to a machine learner, they are not packed with enough characteristic features to make conclusions. Data preprocessing
is an important step in the manipulation of data for compatibility with a ML model. In this case a Fast Fourier Transformation is conducted on each AE hit in order to begin to develop distinguishable features. Once of the most important features for these AE events are the frequency peaks that are obtained after the FFT is completed. These peaks are the main feature which the ML model will learn from.

Fast Fourier Transformation (FFT) is a method used widely in signal processing. It can be conducted with minimal processing power and computation time. The basis of the FFT process is deconstructing a signal into a combination of cosine waves with varying frequencies. This allows for a better insight into the frequency content of the data being transformed. The signals collected during AE collection are very complex time and amplitude waveforms, but by transforming them onto the frequency domain, they can be more easily compared to one another.

Figure 3.2: A graphic depicting how the FFT process changes time domain signals [22]
This can be seen in the work done by Qing-Qing in their comparison of amplitude and frequency domains of different sensor locations [3]. This FFT allows for any signal to have its relative amplitude changes be measured without influence from signals which are symmetric about the x-axis. FFT was conducted in this experiment with the use of a function in MATLAB provided by MathWorks, its input was the time domain signal and resolution required. The signals are then passed through a Hanning window which reduces any spectral leakage which would otherwise be present.

These signals were then vetted by hand in order to determine any outliers present in data. Such outliers may have been caused by a tap of wires or other unexpected source; these signals can easily be found with a visual check of the time domain waveform. The main observations that would lead to an outlier diagnosis are misplaced peaks, too numerous peaks, and too few peaks. The placement of these peaks can be simulated, and signals collected should closely resemble the simulations. These outliers must be removed before the synthetic data generation so that they don’t have any weight on the new data.

Figure 3.3: Graphic showing the transformation process from MATLAB figures to .png files.
The images used in training/testing are created by the use of the Choi Williams Transform (CWT) method, which allows for the use of both time and frequency spectrum in the same image; these images are fed into the GoogLeNet pretrained image classifier. GoogLeNet was chosen due to its compatibility with transfer learning, which allows for a model to learn low level features using hundreds of thousands of prelabeled images, then the studied dataset can be imported for specialized training.

![Image](image.png)

Figure 3.4: Shows a typical 224x224 CWT modified AE signal.

The CWT modified signals have brighter yellow values where peaks overlap and dark blue values where peaks are not present, as seen in Figure 3.4. Type 1 and Type 2 signals carry over their features from the time and domain waveforms and carry distinguishable patterns in the CWT image. These images are optimal for input into a ML model due to their overall simplicity and uniform layout across all samples. These images are generated iteratively without the use of software outside MATLAB, this allows for batches of data to be processed all at once. This improvement was created in response to the previous work of Chandler Garret [9], where an outside software was used to crop
CWT images, adding a large amount of processing time. The automated cropping and saving of CWT images also ensured a uniform output.

The programs used were able to convert entire DTA Files worth of tests within a span of 10 minutes. Above in Figure 3.5 are samples of CWT spectrograms for each specimen type. Each is iteratively pushed through the CWT process and named according to the hit number and DTA file it originated from. This allowed for incoming data to even be transformed while the fatigue testing was still ongoing.

3.3 IMAGE CLASSIFICATION TECHNIQUES WITH SMALL DATASETS

Within many fields of research, a limiting factor for the speed of development is the cost and setup time required for meaningful signal analysis. Most of the cost and setup is due to complicated experiments which need to be conducted in a precise and accurate fashion. This leads to a slow influx of high-quality data. To increase efficiency of collected data many methods have been explored and implemented into signal analysis and machine learning methods. Additionally, due to the limited amount of data that can
be collected during our experiments, there must be methods employed during our ML approach that caters to having a small data set. In practice, image classification models operate on hundreds of thousands of data points for testing and training, but in the case of in-situ experiments, the amount of data that can be collected within a reasonable time frame is limited. In this experiment, only around 200 samples are collected per class. This presents obstacles and hazards when training and testing CNN models. Due to the scarcity of data, each sample has much more impact on the success of the model’s performance. An extreme amount of care must then be applied when collecting and labeling data. Labeling data in this case comes in the form of labeling each AE signals with the crack length it originally originated from, labeling is one of the more labor-intensive facets of supervised machine learning since it takes the efforts initially provided by a human. These labels are ordered in the form of discrete classes, each with a unique label for predictions, these classes and labels are the possible outcomes of the model’s prediction. The classes must also be sufficiently balanced in order to avoid any majority class bias, which could greatly affect accuracy of the ML model. A popular technique to use is to drop data points out of the majority class in to achieve a more balanced set. this was tested using a previously collected dataset containing noise, 3-5 mm signals, and 7-8 mm signals. It was observed that when there was a large discrepancy in the amount of data found in classes, the model had a bias to predict the majority class and funnel all minority class guesses into one of the minority classes. This was remedied by removing data from the majority class until all three classes were the same size. The model then was able to distinguish the minority classes and lost its majority class bias.
One of the methods to be used to remedy the lack of a large data set is to generate synthetic data. This data was created by using the Synthetic Minority Oversampling Technique (SMOTE) technique for data synthesis. This technique was adopted from the research of [10] and utilizes a k-nearest neighbor technique to mimic the patterns of the experimentally collected dataset. This data was created in order to bolster the amount of data that would be included into the machine learning model, as well as bring balance to the experimentally collected dataset in order to reduce any majority class balance found in training. The data synthesized was the windowed signal located in the time domain, these signals were then put onto the frequency domain via FFT.

![Graph showing a synthetically generated AE signal within the time domain.](image)

**Figure 3.6:** Graph showing a synthetically generated AE signal within the time domain.
Figure 3.7: Graph showing a synthetically generated AE signal with labeled frequency peaks.

Figure 3.8: Graph showing an experimentally collected AE signal with labeled frequency peaks.
In comparison to the experimentally collected data, the waveform of the synthetic signal Figure 3.7 is quite similar. The frequency content of the signal shown in Figure 3.8 is also very similar. This synthetically generated point acts as a suitable supplementation of the experimentally collected AE signals, while also addressing the lack of reproducibility of AE experiments.

Synthetic data is a popular method used in order to bolster raw numbers during ML testing and training. This is due to its ease of implementation and ability to accurately mimic the real-world system responses. The method of synthetic data generation used in these tests is by using SMOTE function created by [10]. In simple terms, this function works by first picking a random datapoint in a set, identify the vectors between the selected point and its “neighbors”, augment the vector by a random value between 0-1, and shift the neighbors according to this vector. It is akin to slightly moving each point based on previously collected patterns in “real” data. [17]. The acoustic emissions signals received during the in-situ experiments are converted to a simple time and frequency domain set. The time domain signals can be used with the SMOTE function in MATLAB to synthesize points which are near-identical to “real” signals. Below are examples of the different classes with synthetic time and frequency domain data.
Figure 3.9: Shows synthetic 10-12 mm data and ‘real’ 10-12 mm data in the time domain, and an overlapped frequency domain with synthetic in red and ‘real’ in blue.

Figure 3.10: Shows synthetic 12-14 mm data and ‘real’ 12-14 mm data in the time domain, and an overlapped frequency domain with synthetic in red and ‘real’ in blue.
Synthetic data generated by the SMOTE method is shown in the previous figures, it follows the expected peak locations as well as slight variations in waveforms that is typically seen in ‘real’ data. The synthetic data generated is kept at 25% or less of the entire dataset in order to preserve its authenticity. Synthetic data can greatly improve results in a small dataset since it can add a relatively large number of points that cannot be outliers. However, since it uses a statistical method based on a pool of previously collected data to generate signals. If the synthetic data is introduced into the pool of data being used as a source for generation, it can lead to the possibility of making synthetic data based on synthetic data and can lead to a clone of a clone situation, which is undesirable. This synthetic data was a substitute for experimentally collected data, which saves a very large amount of time and money which would otherwise be spent in lab experiments.
Another method of improving results for a small dataset is to address majority bias. When working with an ML model which uses experimentally collected data one of the most prevalent problems is the development of a majority bias, especially when there is majority towards an overwhelmingly large class. This discrepancy in class size can develop due to the differing success rates of independent experiments; these experiments can cause imbalances within classes. This imbalance leads to a need for balance among all labeled classes. The first case studied is composed of a single majority class with 100% more than the other minority classes. It can be seen that the model learns that the best way to get a low loss and high testing accuracy is to always guess the majority class. This leads to a loss of interpretation of the minority classes entirely. This model may contain many points but is limited by the discrepancy in the amount of data per class.

Figure 3.12: Shows the confusion matrix for a test where the 10-12mm class had (70) samples, the 12-14mm had (35) samples, and the 14-16mm had (35) samples.
Figure 3.13: Shows the confusion matrix for a test where the 10-12mm class had (70) samples, the 12-14mm had (35) samples, and the 14-16mm had (52) samples.

The next case explores the possibility of three uneven classes, one of which is 75% of the majority, and the other is 50% of the majority class. There is a clear distinction that the model predicts the majority and lower majority classes without attempting to guess the minority class. The model does this since by operating this way, it can achieve its highest possible testing accuracy on every iteration of learning.

Figure 3.14: Shows the confusion matrix for a test where the 10-12mm class had (80) samples, the 12-14mm had (80) samples, and the 14-16mm had (80) samples.
The third case in Figure 3.14 is an example of a perfectly balanced distribution between classes. It can be seen that the model is able to learn all three without developing a bias towards any one class. By avoiding a majority bias, even a lower amount of data per class can lead to a better performing ML model. This is shown by case four, where the amount of data is the same as case 3, but data is distributed evenly among the three.

One of the most common issues with ML models and experimentally collected data is the monetary and time limitations of conducting experiments. The amount of data collected is very useful when increasing the performance of a classifier model, but the amount added becomes less impactful as more data is in the total set.

Figure 3.15: Shows the confusion matrix for a test where there are 60 samples per class and an achieved 63.33% test accuracy.

In order to increase the performance of a ML model which classifies AE signals, methods were implemented from literature which are known to help smaller datasets. These methods were class balancing and synthetic data generation. Class balancing allowed for the model to learn each class more evenly and take out any training bias. And synthetic data generation could bolster the raw number of samples per class or be used to specifically target ranges where data was scarce. This effect can be seen when
comparing Figure 3.15 and Figure 3.16. These were identical GoogLeNet models with the same setup, the difference being the amount of data in the dataset. The model with 80 samples, improved its accuracy by almost 20%.

Figure 3.16: Shows the confusion matrix for a test where there are 80 samples per class and an achieved 88% test accuracy.

3.4 CNN MODELS FOR IMAGE CLASSIFICATION

In order to achieve best results, a model had to be carefully selected by testing and comparing various models on a small dataset. These models were selected based on two requirements, firstly they must be an image classifier that has been pre-trained on images in order to have low-level feature training completed before the AE data was inserted. Second, they must have a low number of layers and “complexity” as any model that is too complex could lead to quick overfitting.

Within the field of data science, a machine learning classification algorithm has the ability to “learn” correlations between labels and sets of corresponding images. The model is then able to place these labels based on the learned features of the previous sets.
They have become a driving force in many technical fields, and their applications seem to continue growing in magnitude. These models become extremely useful when applied to SHM. By being able to determine the possible sources, seriousness, and location of microcracks, corrosion, and one of the many other types of defects or damage. These classifiers have been applied before in the field of acoustic emission research where a classifier was able to accurately determine if an AE Hit event originated from a crack, or “noise” [9]. This was done by the same method of AE collection apart from a 1 mm initiation hole being the initiator for fatigue cracks to grow from. This experimental data was provided by Chandler Garret and the same classification goal was performed, except in this case, it was GoogLeNet that performed the classification in place of AlexNet.

![Confusion matrix showing results from Crack vs Noise Classification](image)

**Figure 3.17**: Confusion matrix showing results from Crack vs Noise Classification

According to Figure 3.17, GoogLeNet was found to have outperformed AlexNet in its noise vs hit classification in terms of accuracy. This could be due to its relatively newer framework methodology in its convolutional layers.
CNN models are extremely powerful and efficient tools which are capable of the classification of sometimes hundreds of premade labels. The networks have complex structures and are a form of deep learning model where interconnected layers relay information through the model framework. CNN models have been found to be extremely compatible with the study of acoustic emissions and outperformed other typical ML models such as clustering methods, RNN, and ANN models [13]. However, these CNN models have a lengthy training time and high computation costs [13]. The CNN models selected after this screening were Alex-net, GoogLeNet, SqueezeNet and Inception Res-Net v2. Out of these models, GoogLeNet performed best on a training/testing series performed on previously collected data. The metrics used for determining the model results were training time, testing accuracy, training accuracy.

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Time</th>
<th>Test &amp; Train Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogleNet</td>
<td>8-minute</td>
<td>100% Test &amp; Train accuracy</td>
</tr>
<tr>
<td>Inception ResNet-3</td>
<td>44-minute</td>
<td>100% Test &amp; Train accuracy</td>
</tr>
<tr>
<td>AlexNet</td>
<td>2-minute</td>
<td>50% Train &amp; 36% Test accuracy</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>3-minute</td>
<td>46% Train &amp; 30% Test accuracy</td>
</tr>
<tr>
<td>VGG-16</td>
<td>15-minute</td>
<td>N/A Test &amp; Train Accuracy (loss function unstable)</td>
</tr>
</tbody>
</table>

Figure 3.18: Results of multiple ML models training and testing performance.

GoogLeNet is a pre-trained, 22-layer, simplistic ML model which has been recommended in literature for use with small datasets. The GoogLeNet architecture uses a stochastic gradient with a relatively low momentum of 0.9 and a fixed learning rate. GoogLeNet was developed by researchers at google for the LSVRC 2014 competition.
where it won first place in a performance evaluation. The GoogLeNet used on this competition set a new standard for the performance of CNN models within data science.

The methodology involved in machine learning calls for two main ideas that are both of the upmost importance to the success of the machine learning implementation. The first is the dataset, the dataset is like the fuel for the ML model, it is what the human minds can set as guidelines for a machine to learn by. Without a quality dataset, any machine learning endeavor is doomed to fail before it even starts, as it portrayed in the popular computer science saying, “Garbage in, Garbage Out”. The second main component of the machine approach is the Model involved. The model is the framework and approach the method chooses to learn the given material. Different models can massively influence the performance of a machine learning approach since it directly controls what the model is choosing to learn and predict.

Many methods are used in order to optimize the main features of the dataset being used. These main features are the labels, class sizes, and data format. The labels of the machine learning model depict what each data point truly is and also what the machine learning will be able to choose as a prediction. In this experiment, the labels are {10-12 mm, 12-14 mm, and 14-16mm}. These labels were determined after the thoughtful planning of possible experiments, the labels contain a range of crack length in increments of 2 mm, these increments were found to be large enough such that there will be sufficient amounts of data per label, yet small enough to be useful for application. Another important note about the labels is about the amount of precision and accuracy used when labeling each datapoint. Data must be labeled with utmost care in order to give
true classifications of each piece of data, otherwise, the model may become confused during the training process.

The class size is an important component when using a Machine learning model, generally, the more data once can collect, the better. In this experiment, the amount of data collected will be limited by the speed of the in-situ experimentation. The class sizes also must be within reasonable reach of one another, as a bias could develop during training.

Data format is another of the key aspects of a dataset, the format of the data changes many times between the initial collection, interpretation, processing, and input into the ML model. These changes are typically chosen on what features are being studied and deemed important, as well as what the ML model is using for input. For example, this experiment initially collects time series data, which is then converted to the frequency domain using FFT, transformed by the CWT process, and finally resized into an acceptable image size and format. It is imperative that the data is not only closely watched as it is transformed from one state to another, but the transformations must be homogenous through the entire set. The programs and software used for these transformations are carefully placed into synchronization with variables such as the sampling rate, capture window, and noise canceling applied.

The ML model being used is chosen based on many factors that are specific to the problem set and desired results. There are two basic types of machine learning models, either it is a supervised model, or it is an unsupervised model. Unsupervised models are
models which are simply given unlabeled data and are capable of clustering and
determining patterns which are too fine for the human eye.

Supervised models are given labeled data and use the labels as guidelines for training. Supervised models also contain subcategories which are regression, and classification. The main difference between regression and classification is the use of discrete classes by the classifier, while regression models rely on continuous data to make predictions.

The use of a classification model in this study is a place for future improvement: it was found that collected data would sometimes not be regularly spread over the duration of crack growth, and small clusters of data would form. A regression method would be extremely useful in this case since the dataset is a continuous value, and while a classifier is still accurate and dependable, a regression model would be able to interpolate between class labels easier and give a more accurate prediction. The difficult stemming from creating a regression-based model is the ability to create labels which are extremely precise, as well as containing enough finely labeled data to cover a large range.

In previous experiments, only one of the PWAS had its signals analyzed and processed for machine learning. This allowed for around 40 signals max to be collected during the growth of a 2 mm crack. This method of crack generation would be timely when compiling an entire database of acoustic emissions, especially when a dataset must have at least 100 samples per class to get viable results [21]. The experiments however each contain four bonded PWAS all of which are capable of the same quality of data collection. In recognition of this, signals from all 4 PWAS are added into the
training/testing dataset, effectively quadrupling the amount of data collected from a single specimen. The signals received at PWAS 3 and PWAS 4 are nearly identical while the same is true for PWAS 1 and PWAS 2. The signals collected at PWAS 1,2 contain different time domain signals but can be corrected by the introduction of a small delay. Once the delay is introduced, the FFT signals have similar peaks as the PWAS 3,4 signals. Based on this information, the signals were determined to contain enough similar information to be used within the same dataset. This hypothesis was tested when a model containing signals with all 4 PWAS was put loaded into the same GoogLeNet framework, and the model achieved a 90.6% testing accuracy. Which is above the accuracy threshold for viability.

Long Short-Term Memory (LSTM) models are models specialized in the application of time series data. They can learn patterns found in data and have been used widely in acoustic environments in the past. This model would change the format of the data used within the classifier, since it would be used with the windowed, noise reduced signals, as opposed to CWT spectrograms. The use of the frequency domain is also possible with these LSTM models. The Deep Learning Toolbox also has a layer capable of “flattening” any input images, which can be used with the CWT images, this model was tested using the four PWAS dataset and was found to have an accuracy of 85.6% for testing. By utilizing the ability of workspace storage found on MATLAB, a dataset can be created and tested with the three different methods of data input, frequency domain, time domain, and CW flattened inputs. Another interesting model framework to study is the use of CNN- LSTM hybrid models, these models take attributes from both CNN and
LSTM models, they generally work with spectrograms much like what is found in the AE data collected.

3.5 TRAINING AND TESTING OF RELEVANT ML MODELS

Figure 3.19: Accuracy and Loss curves for GoogLeNet Training

Post processing of testing and training results is an important step in creating a usable ML model, typically, a training curve is one of the first ways to determine whether or not a model will be viable. Training curves within the Deep Network Designer toolbox in MATLAB are updated real time with both a validation, training(smoothed), and training curve, as well as a loss curve containing the same segment types. These training curves give the user a lot of valuable information about how well the model is adjusting to training, and if the model should not fully mature due to an early lack of accuracy increase.
The testing results processing comes in this case in the form of a confusion matrix, these matrices display the true and predicted values of the testing set in an easy to digest form. For a balanced model, a confusion matrix and basic accuracy calculations are an acceptable method of interpretation.

During the training of the GoogLeNet model with the 4-PWAS dataset, there was a total of 30 epochs; epochs meaning the amount of time the data was passed through the total network for training. The training accuracy reached 100% at around 23 epochs taking a total of 37 minutes and 12 seconds. Which is quite a lengthy period for a single training event, this is due to the complexity of CNN type models when compared to other network types. The accuracy and validation curves do seem to separate at one point during training, but they never separate more than 10% for training accuracy which is an acceptable level.

![Confusion matrix for GoogLeNet Model](image)

**Figure 3.20: Confusion matrix for GoogLeNet Model**
The confusion matrix for the GoogLeNet model and 4-PWAS shows a testing accuracy of 90.7%, which is considered an excellent classification model. This model was trained on 70% of the set as training, 20% as testing, and 10% validation.

![Image of confusion matrix](image)

Figure 3.2: Accuracy and Loss curves for LSTM Training

This is the training and loss curve for the primary LSTM model, which used the same CW transform images, but applied a flattening layer before the LSTM layer. The model trained to an accuracy of 77.5% for both training and validation, the curves for which were almost identical. The training was run for 50 epochs and took 6 minutes and 2 seconds to fully train, which is many times faster than that the CNN model took to train. This is due to its low number of layers and overall model complexity.
Figure 3.2: Confusion matrix for LSTM model

The confusion matrix for the LSTM network tested at an accuracy rate of 85.27%, which is still considered a viable model. It was tested and trained with the exact same dataset, split in the exact same fashion as the GoogLeNet model. Showing that the GoogLeNet model was ultimately more accurate.

3.6 SUMMARY AND CONCLUSIONS FOR CHAPTER 3

The methods for model performance increases have been discussed and applied to the model and dataset. And the image processing and signal analysis has been optimized for large batches of data and ease of use. Which allows for quick conversion of AE waveforms into usable CW transformed images. After all ML models have been ran it was concluded that the most robust and accurate model is the GoogLeNet model trained with the 4-PWAS dataset. This model reached an accuracy of 91% and was able to distinguish AE hits undetermined by distance away from the AE source. This model could be used with two different sensor placement patterns for a slit specimen. The
LSTM model types were also able to conduct classification on the same dataset, but at a lower accuracy of 85%. The training time for the GoogLeNet model was found to also be much higher than that of the LSTM model, but the added 6% of testing accuracy is worth the extra time in the opinion of the author.
CHAPTER 4
SUMMARY, CONCLUSIONS, AND FUTURE WORK

4.1 SUMMARY AND CONCLUSIONS

In brief summary, a series of fatigue experiments was conducted where a thin aluminum sheet was equipped with 4-PWAS and a hair thin slit at its geometric center. The experiments aim was to collect Acoustic Emissions, which are signals that are generated from crack advancement or crack rubbing. The method of AE generation was a low cycle fatigue experiment with loading governed by a constant SIF value. Once these signals were collected, they were post processed and used for the training of a set of machine learning models, which consisted of a CNN model and an LSTM model. The LSTM model was based on flattened CW transforms. The CNN model performed with higher test accuracy than the LSTM model and was found to be an excellent classifier of the AE data from the three classes (10-12, 12-14, 14-16). The accuracy of the CNN model (GoogLeNet) allows for it to be considered a “near perfect” classifier since it tested above 90% accuracy.
4.2 FUTURE WORK

One future aspect of this work that could be improved upon is the inclusion of different test Specimen types for data collection (single bolt lap joint, riveted lap joint, composite materials). These different types begin to simulate real world aerospace structures more accurately. These methods have been discussed within LAMSS meetings and even fabricated for testing, but no AE have been collected as of this thesis. These testing plates would be constructed as according to industry standards, especially the riveted and bolt lap joints, as they are the most mechanically complicated. The lap joint specimens would also need different AE filtering procedures since the PWAS would have to be placed on different lengths from the initial fatigue crack source. The composite type testing specimen would also be interesting since it would be the study of AE within an anisotropic medium. Which would add directionality to the propagation of elastic waves. This directionality would change the PWAS responses according to where they were located on the testing specimen.

Regression based ML models. Since the length of a fatigue crack is a continuous value, a regression-based model which can classify on a continuous scale would add even more insight into the current. The current class labels span a range of 2 mm, which means a 13.9 mm long fatigue crack could potentially be classified as a 12-14 mm crack without being signaled as being extremely close 14 mm crack. This discrepancy would be resolved if a regression model could be applied to the model. The difficulty here comes in the labeling process of the crack and AE hit, it could be possible to couple these two
values for accuracy in the form of object detection ML models, or other means to precisely determine at which point an AE event is captured.

A third improvement that could be made to this work is the addition of multiple PWAS phase array patterns. These patterns would allow for data collection in hopes of a model without directionality, the four PWAS dataset introduces a small amount of directionality, but by changing the array entirely, a model could be created that could identify AE from any angle.
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APPENDIX A

BONDING PWAS USING M BOND AE 15

Items needed:

- Curing agent 15 jar
- Resin AE jar
- Weighing scale
- 600-grit sandpaper
- Cloth gauze
- Degreaser
- Disposable pipette
- Cotton Q-tips
- Tape
- Acid & Base
- Metal scraper/marker tool
- Glass stirring rod.
- Disposable mixing tray

** wear lab gloves throughout this whole process **

Directions:

Preparing the aluminum substrate surface:

1. Have the following items readily available for this section: 600 grit sandpaper, cloth gauze, degreaser, cotton Q-tips, tape, acid & base, metal scraper/marker tool,
2. Mark on your substrate specimen where you wish to bond the PWAS with the metal scraper. NOTE: it is best to have lines that extend far out drawn in sharpie creating a cross where you wish to bond the PWAS. This is because the mark that you create with the metal scraper and the sharpie in immediate area of the bonding point will fade during this surface preparation procedure.
3. Using the 600-grit sand paper, sand down the area where the PWAS will lie, making sure to sand in all directions thoroughly.
4. Using the degreaser and cloth gauze, spray and wipe down the spot where you have sanded thoroughly. Repeat the spray and wiping until no residual mark of dirt or any other substance appears on the gauze after wiping.
5. Spray the spot with the degreaser and wipe using a cotton Q-tip to again ensure no residual mark appears on the Q-tip.

6. Place a drop of acid (red cap) on the location and rub in with a new cotton Q-tip. Allow to dry or dab to dry using a new cloth gauze, but do not wipe back and forth, so as to avoid moving dirt or other undesired contaminants to the clean area.

7. Repeat Step 6 using a drop of the base (blue cap).

8. Once this surface preparation is completed, place the PWAS directly onto the location and tape it down.

9. Your PWAS bonding location is now prepared for the adhesive application.

Mixing the adhesive:

1. Have the following items readily available for this section: Curing agent jar, Resin jar, weighing scale, disposable pipette, glass stirring rod, disposable mixing tray.

2. Turn the scale on and ensure that it is “zeroed” with nothing placed on it. The “T” button on the scale can be used to zero at any time.

3. Place one plastic disposable mixing tray on the scale, allow it to reach a steady state reading of weight, then zero it using the “T” button.

4. Open the jar of Resin AE, and slowly pour/place resin into the try while it is still placed on the scale. This process is done easiest using the glass stirring rod as a mean of transferring small amounts at a time from the jar and letting it fall off the rod into the tray. Do this until 1.25 grams has been placed in the mixing tray.

   NOTE: if 1.25 grams is accidentally exceeded, the stirring rod has proven to be a useful tool in removing excess from the tray. Simply place the stirring rod into the reservoir of resin in the tray and allow some to stick to it, then remove, as needed.

5. Once ~ 1.25 grams is achieved, zero the scale using the “T” button.

6. Open the jar of curing agent 15, and acquire a plastic disposable pipette from the bag.

7. Place the pipette into the jar of curing agent and gather an ample amount in the pipette.

8. Place, drop by drop very slowly, curing agent 15 into the mixing tray which already has the reservoir of resin in it. Place the drops directly into the center of the reservoir of resin. Do so until the scale reads 0.1 grams.

   NOTE: it has been noticed that a single drop coming from the disposable pipette is around ~ 0.02 grams, so consider this while estimating how many drops will be placed.

9. Once the resin and curing agent have both been added to the mixing tray, remove it from the scale and mix the components while tilting the tray to one side, so as to have all the fluid fall to one area for optimal mixing. Mix thoroughly for 6 minutes.

10. Your reservoir of M Bond AE 15 is now ready for application.

Attaching and Curing the PWAS:
1. Fold back the tape and PWAS placed in Step 8 of the surface preparation section. Ensure that the PWAS remains adhered to the tape as you fold it back.

2. With the tape folded back, use an object with a small tip (i.e. Glass stirring rod, metal scraper/marker tool, etc. The sharper tip the object, the easier it is to place a small drop) to gather a small drop of adhesive from your reservoir. Place this drop of adhesive directly onto the location where the PWAS will be bonded, and where it was before being folded back with the tape.

3. Fold the tape back over the drop so that the PWAS gets placed onto the adhesive.

4. Place the appropriate amount of deadweight on the PWAS [5-20 psi, 35-135 kN/m^2]

5. Place the PWAS into the oven and cure based on the cure cycle shown in Figure 1.

![Figure 1: Curing Cycle](image)

(NOTE: Added cure time with the temperature being gradually reduced back to room temperature is optimal.)

6. Remove the specimen from the oven and remove the deadweight and tape.
7. Your PWAS is bonded and ready to be used.

**Removing a PWAS:**

1. Using a rubber mallet and screwdriver, gently chip off the PWAS from the surface.
2. Apply a small amount of Isopropyl Alcohol and use sandpaper to remove excess adhesive.
APPENDIX B

MTS MACHINE START UP AND PACK UP STEPS

***NOTE***: If anything wrong were to happen during testing, there are four big, red emergency stop buttons; one on the control panel, one to the right of the desktop, one to the right of the crosshead bar controls and one on the oil tank to the right of the machine.

Grip Installation

In order to utilize the MTS machine with 4-inch grips, you must first unhook the springs from the current grips installed into the MTS machine. You must place the 4-inch grips into position on one of the housings on the MTS machine. Make a U-shape out of some of the metal wire (DO NOT CUT ANYTHING) and snake it through the hole on the top of the grip itself.

Then using the metal wire, attach the end of the spring to a length of the wire by making a U shape and applying a small amount of tension, pulling the spring up into the grip.

A second person must then use the small screw that was taken out of the grip and install it back into the side where the spring is being pulled through. Check to ensure that the spring has been secured inside the grip and onto the screw. There should be very little wiggling when you pull on the grip. Repeat this twice for all 4 grips that need to be installed.

Start Up:

1. If not already open, open ‘Shortcut to user’ on desktop and enter username and password
   a. Username: user
   b. Password: user
2. Open ‘shortcut to TWSX’
3. Open an existing template (twsx → roshan → fatigue test)
4. On control panel, if Interlocks have any lights on, hit the reset button.
5. Turn on MTS machine by pressing “low” then “high” for HPS Control first and then HSM Control
6. Turn on water flow to keep oil cool (black button)
7. Unlock crosshead lift, move top grip to the desired height and lock it again before moving the bottom grip
8. Turn on Actuator Positioning Control to move the bottom grip
9. Turn off Actuator Positioning Control to switch to enable force mode.
10. Check to make sure the MTS machine is in the 5,000 lbf load cell (Display → Input Signals → select drop down arrow to select 5,000 lbf)
11. Close top wedges on top of specimen using hydraulic controls (turn the top left knob all the way to the right, then turn bottom left knob to the left)
12. Before closing the bottom wedges on bottom of specimen, zero the MTS machine cell (Display → Input Signals → select ‘A’)
13. Make sure to apply a low load right away to reduce load fluctuation
   a. Recommended:
      i. End level = 80 lbf
      ii. End level 1 = 60 lbf
      iii. End level 2 = 100 lbf
      iv. Frequency = 4 Hz
      v. Cycles = 10

Pack Up:
1. Apply low load as recommended above at #13
2. Make sure the interface is on edit mode, NOT execute (this allows displacement mode to be enabled)
3. Once cycles are complete, turn on and off the Actuator Positioning Control to put the MTS machine into displacement control mode
4. Release the bottom wedges using hydraulic controls (turn bottom right knob all the way to the right, then turn top right knob to the left)
5. Holding onto the specimen, release the top wedges using the hydraulic controls (turn the bottom left knob all the way to the right, then turn top left knob to the left)
6. Turn off MTS machine by pressing “low” then “off” for HMS Control then HPS Control
7. Turn off water flow (red button)
APPENDIX C

PROCEDURE FOR PLB TESTING

**Equipment needed to perform PLB.**

1. Special Mechanical pencil with PLB attachment (Figure A.2)

2. Mistras AE collection hardware/software (Figure 2)

3. Mistras 2/4/6 Preamplifier (Figure 3)

4. Specimen with PWAS and coaxial cables attached (Figure 5)

5. Flat Surface with rigid wood block support (Figure 5)

![Special Mechanical Pencil with PLB attachment](image_url)

**Figure A.2:** Special Mechanical Pencil with PLB attachment
Figure A.2: Cart Holding AEwin Hardware

Figure A.3: Mistras 2/4/6 Preamplifiers
To physically conduct PLB

1. Place specimen on flat surface with wood block support
2. Begin acquisition on AEwin software
3. Push out about 3 mm pencil lead
4. Apply pencil lead with a small amount of force at an angle until the lead breaks, apply as close to the expected crack tips as possible
5. Conduct multiple tests at either approximate crack tip to check symmetry
These PLB tests should be done at the end of the bonding/soldering process as well as intermittently during fatigue testing. This ensures that the sensors have not been damaged and the signals being received are crisp. The experimental setup is shown in Figure 6.
1. Plug Coaxial cables from PWAS to channel inputs 1-4, make sure to match the PWAS number to the Channel number.

2. Open the AEwin software and apply the default settings within the hardware settings as well as graphical layout, this can be done by hitting file> open layout> default (Figure )

![Figure A.7: AEwin Default Settings](image)

3. Hit Acquire (Figure 8), name the file, and conduct the PLB, then hit stop acquisition.

![Figure A.8: Acquisition collection buttons (Play, Pause, Stop, Acquire)](image)

4. The PLB from 4 channels were collected as shown in Figure 9. Then replay the file that was saved from the acquisition. Use the Green Select Interface button (green box) and inspect the AE hit marked by the red boxes on the channels.
5. Compare both the Amplitude and Time of Flight at each channel (Figure 11). This is done by using the green box and viewing the waveform of the AE hit. Amplitude should be higher, and TOF should be sooner for the PWAS that are closer to the specimen, rather than the outer PWAS.