Crack Detection Using Combinations of Acoustic Emission and Guided Wave Signals from Bonded Piezoelectric Transducers

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ABSTRACT

Piezoelectric transducers are broadband devices and can operate over a large frequency range. In structural health monitoring (SHM) applications, piezoelectric transducers are commonly operated at ultrasonic frequencies to excite and sense guided waves, detect acoustic emission (AE) events, and record electro-mechanical impedance (EMI). The transducers can also measure lower frequency information, such as strains resulting from operational loads or vibrations due to environmental factors. This paper presents a crack detection experiment using piezoelectric transducers to provide signals measuring guided waves, AE events, EMI, and strain. The experimental test articles are aluminum dogbone coupons. Each coupon has a small hole drilled in the gage section to serve as a crack initiation point. Each coupon is instrumented with two transducers, both on the same face of the coupon and on either side of the gage section. Each coupon undergoes cyclic tensile loading to initiate and grow fatigue cracks. At various intervals, the fatigue cycling is paused and the coupon is visually inspected for crack initiation and growth. While the cycling is paused, guided waves are generated and sensed by the pair of transducers; each being used in turn as a transmitter or receiver. In addition, EMI measurements at each transducer are made with the cycling paused. Ideally, AE and strain measurements would be made continuously during the cycling. However, for these studies the available hardware did not allow continuous collection of data. As a result, the AE and strain measurements also are taken over limited time segments while the primary fatigue cycling is paused. Collection of data for the various sensing modes continues as the crack grows to the point of coupon fracture. Baseline crack detection performance is established using statistical pattern recognition methods applied to the guided wave data. Additional crack detection algorithms are designed and evaluated to demonstrate the potential benefits of using decision fusion methods applied to combinations of guided wave and AE data. Artificial AE data has been utilized since the current testing hardware did not allow for the collection of useful AE data. Future studies will address the collection of AE data and consider data fusion incorporating EMI and/or strain data.

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INTRODUCTION

Structural health monitoring (SHM) is the term given to a process for automatically assessing the status of a structure. The needs for, and benefits of, SHM systems for civil, military, and aerospace applications have been documented by a number of researchers [1-3]. A common approach for designing SHM systems begins by characterizing the healthy state of the structure using baseline measurements [4]. The SHM system compares test measurements to the baseline measurements and computes an estimate of the current structural state. The comparison between baseline and test measurements is a pattern recognition problem.

Typically, a pattern recognition SHM process accepts as inputs signals obtained from dedicated sensors, usually permanently attached to the structure. These signals may be processed to emphasize aspects of the signals related to structural condition. Metrics are computed from the processed signals. The metrics are then passed to a computational comparison stage, in which a decision is made regarding the state of the structure.

Experimental testing has been performed on aluminum dogbone specimens with bonded piezoelectric transducers. The objective of this effort is to demonstrate the detection and length estimation of fatigue cracks, a common damage mechanism observed in air vehicle structures, using a combination of acoustic emission and guided wave signals provided by the piezoelectric transducers. This paper considers fusing multiple types of information or decision systems in the SHM process to improve performance.

A short review of piezoelectric sensing for SHM is given in the next section. The experimental testing is discussed in the following section. Next, the designs of crack detection and crack length estimation algorithms are presented and results of the algorithms are shown. Finally, a discussion is given and conclusions are made based on the results.

PIEZOELECTRIC SENSING FOR SHM

Piezoelectric transducers are the most commonly used transducers for SHM applications [1]. A variety of piezoelectric materials are commercially available, but transducers made from the ceramic lead (Pb) Zirconate Titanate (PZT) are widely used. PZT transducers are broadband devices and can operate across a large frequency range. For these studies, bonded PZT transducers are utilized in the ultrasonic frequency range to sense acoustic emission events and to excite and sense guided waves. In addition, the same transducers are utilized in the ultrasonic frequency range to record the coupled electro-mechanical impedance of the bonded sensors, measurements which are useful for SHM as well as to verify sensor and bond integrity. Lastly, the PZT transducers are also utilized to track the lower frequency mechanical strains created during fatigue loading.

Acoustic emission (AE) principles have been used for a wide range of purposes for at least 70 years [5]. AE signals are generated due to the sudden changes in stress fields created when a solid deforms or fractures [6]. This sudden change in the stress field creates stress waves, also called elastic waves or acoustic emissions.

The waves travel through the structure and can be detected by ultrasonic transducers. AE sensors can operate as narrowband (resonant) sensors or as broadband (non-resonant) sensors. Typically, AE sensors operate continuously with the data processed to count the number of "events" where the sensed data exceeds some predefined threshold. Automated detection of fatigue cracks using AE signals has been demonstrated in the laboratory [7,8]. However, in fielded applications the AE signals can be obscured by a variety of strong noise sources, including fretting, hydraulics, and electromagnetic interference.

Guided waves are similar to the AE signals in that elastic waves are created when particles in a material are elastically displaced. For aerospace SHM applications with plate-like and shell-like structures, Lamb waves are commonly used where the boundary conditions act to "guide" the elastic waves. Guided elastic waves have been considered for SHM for over 50 years, with introduction of the concept to use Lamb waves for damage detection generally credited to Worlton [9,10]. For SHM, active or passive monitoring of guided waves can be utilized, with active monitoring performed in either a pitch-catch or pulse-echo mode. Passive monitoring involves simply monitoring for guided waves generated by an external source (impact, operational loads, etc.), whereas active monitoring involves using a transducer to excite the structure. In a pitch-catch mode, the structure is excited at one transducer and sensed at another, whereas excitation and sensing occur at the same transducer in the pulse-echo mode.

Electro-mechanical impedance (EMI) is a technique that can be utilized not only to assess the status of a structure [11], but also to assess the health of a PZT transducer and the integrity of the bond between the transducer and the structure [12]. In general terms, impedance refers to the opposition of a system to being driven and is a function of frequency. Electrical impedance is defined as the ratio of voltage to current, and mechanical impedance is the ratio of force to velocity. When a transducer is bonded to a structure, the electrical and mechanical impedances are coupled. Any change in mechanical properties close to a transducer, possibly due to structural damage, PZT degradation, or PZT debonding, will affect the EMI measurement response.

Lastly, the PZT transducers can be utilized at lower frequencies to record the strains created in a structure of interest. As with the EMI measurements, the transducer would need to be sufficiently close to any structural damage to sense any change, or the damage would need to be sufficiently large to affect the loads at the transducer location. Even if not useful for damage detection, strain measurements may be useful for loads monitoring to understand the actual load history experienced by the structure.

EXPERIMENTAL TESTING

Experimental testing has been performed on two dogbone coupons fabricated from 0.25 in thick 7075-T351 aluminum. The basic geometry of the dogbone coupons is shown in Figure 1(a). The 7075-T351 alloy was chosen since it is commonly used in aerospace structures. The dogbone geometry has been chosen to

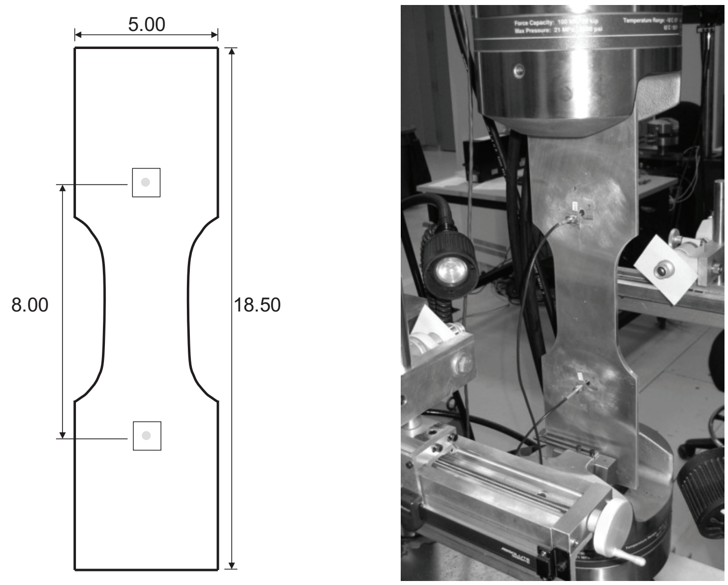


Figure 1. (a) Geometry of dogbone coupons used for experimental testing and (b) aluminum dogbone coupon in MTS load frame

increase the stresses in the gage section, while limiting the strains in the grip regions where the piezoelectric sensors are located. A small, 0.0625 in diameter hole has been drilled in the center of each specimen to further increase the stress at this location, such that fatigue cracking initiates in a known region.

The dogbone coupons are fatigue cycled in a MTS 22 kip load frame, as shown in Figure 1(b). The cycle rate is 10 Hz, with a maximum load of 14,500 lbf and a stress ratio of R=0.1. The maximum load is chosen so that the strains in the grip region remain below 1500 μstrain to reduce the possibility of sensor or bond failure Fatigue cycling is paused periodically to allow visual and SHM inspections of the coupons. A travelling microscope is used to measure visual crack lengths. The visual crack length measurements are used for "truth" data during development and testing of SHM crack detection and crack length estimation algorithms.

For SHM inspections, two Kapton encapsulated piezoelectric transducers are surface-mounted to one side of the dogbone coupons at the locations shown in Figure 1(a) using Vishay Micro-Measurements AE-10 epoxy. The two PZT transducers are utilized for all of the SHM sensing including guided wave, AE, strain measurements, and EMI. LabVIEW programs have been written to automate the data collection process for each sensing mode. Details on the measurement schedule, and mechanical and electrical parameters used for collecting each mode, are described below.

Prior to fatigue loading each coupon, guided wave, AE, and EMI measurements are collected to establish baseline conditions for the healthy structure. Each coupon is then cycled for 10,000 cycles and visually inspected.—This process is repeated until crack initiation is observed, at which point inspections and measurements are performed every 5,000 cycles. The interval between inspections is subsequently decreased as the crack grows, with inspections every 2,500 cycles used after a 0.5 in crack is observed and every 1,000 cycles after a 1.0 in crack is observed. This interval is continuously reduced to as few as 200 cycles to insure testing at a sufficient number of crack length conditions.

Ideally, AE signals would be collected during the entire fatigue cycling process and the number of times an AE event occurred (i.e. when the sensor response exceeds some predefined threshold level) would be counted. Unfortunately, the available hardware for this testing does not permit continuous collection of the AE data. At each measurement interval, AE signals are sampled at 5 MHz under a tensile load increasing monotonically from zero to 14,500 lbf over a 250 ms interval. This process is repeated five times at lower numbers of cumulative fatigue cycles and 25 times at higher numbers of cumulative fatigue cycles. As discussed in the following section, the AE signals collected using this process are found to be of limited use.

Guided wave signals are collected with the coupon unloaded and under a static tensile load of 7,250 lbf. A 5½ cycle, Hamming windowed sinusoidal excitation signal at frequencies ranging from 50 kHz to 500 kHz, in 50 kHz steps, is sent to one transducer. Response signals are collected at the other transducer. Synchronous averages of 20 bursts at each frequency are sampled at 10 MHz over a 300 μs interval. Each transducer is used as a transmitter and receiver. The guided wave response signals are seen to vary as the crack grows.

EMI signals also are collected with the coupon unloaded and under a static tensile load of 7,250 lbf. A SinePhase 16777k Impedance Analyzer is used to measure the EMI of each transducer over the frequency range from 10 kHz to 500 kHz. As noted above, crack detection using EMI measurements assumes that the cracks are significant enough to affect the mechanical impedance around the PZT transducers. This is likely not the case for the dogbone coupons tested; however, the EMI measurements may help verify the integrity of the PZT transducers and bonding.

Lastly, strain signals are collected during cycling loading, with a maximum load of 14,500 lbf, a stress ratio, R=0.1, and a cycle rate of 5 Hz. The transducer responses are sampled at 50 kHz over a 10 s interval. These limited cycles are not included in the overall cumulative cycle count. As with the AE measurements, it might be useful to collect strain measurements during the entire fatigue cycling process; however, this is not practical with the available hardware.

CRACK DETECTION AND LENGTH ESTIMATION ALGORITHMS

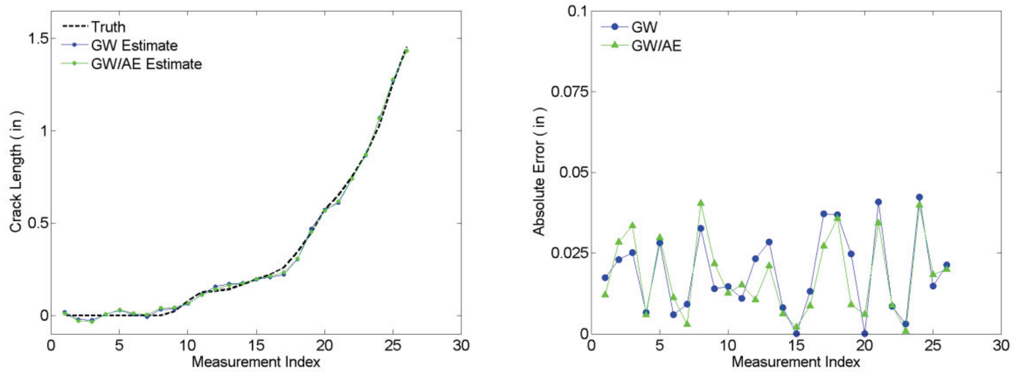
A total of 40 dogbone coupons have been fabricated, but to date only two coupons have been instrumented and cycled to failure. Measurements from the first coupon are used to design the detection and length estimation algorithms, with the algorithm~~s~~ evaluated using data from the second coupon. As discussed above, the guided wave response signals seemed to vary with differing crack lengths. The AE, EMI, and strain signals, however, appeared to be of limited use in detecting cracks. Therefore, initial crack detection and crack length estimation algorithms are based on the measured guided wave data. The approach used for crack detection and analysis in this paper involves choosing a set of design data, computing a pool of candidate features from the sensor responses in the design set, selecting a set of features most useful for crack length estimation, and then fitting a regression model for measured crack length to the selected set of features. These steps are discussed below.

Using guided wave data from the first coupon as the set of design data, definition of a pool of candidate features begins by identifying time segments in response signals suitable for future analysis. The pitch-catch guided wave responses at each excitation frequency are visually examined at the zero cycle count, 7,250 lbf load condition. For the ten excitation frequencies, 15 time-of-arrival intervals have been identified as candidates for possible direct path arrivals of symmetric and anti-symmetric Lamb waves. For each frequency and time-of-arrival pair, a feature is computed from the correlation coefficient, ρ, between the test signal and a reference signal. The reference signal is a measurement stored when the coupon is in a known condition, the zero cycle count healthy condition for these studies. The correlation coefficient measures changes in wave shape or time alignment between two waveforms. For convenience, the value $(1-\rho)$ is used as a feature, since this value is near zero when there is little difference between the waveforms and increases as the difference between waveforms increase. Therefore, the feature value is positively correlated with crack length. One feature value is computed from each frequency, time-of-arrival, and transducer. The ten frequencies, 15 intervals, and two transducers provide a set of 30 candidate features.

Feature selection is based on a stepwise regression procedure [13]. The procedure involves iteratively fitting a series of multi-linear regression models to crack length measurements using different subsets of elements from the feature vector. The subset of features grows or shrinks based on the significance of a feature's contribution to the regression model. A feature is added to the subset only when its presence in the model improves the fit. Conversely, a feature is removed from the subset when its absence does not degrade the fit. The stepwise procedure terminates when the additional of any remaining feature does not improve the fit and the removal of any previously selected feature degrades the fit.

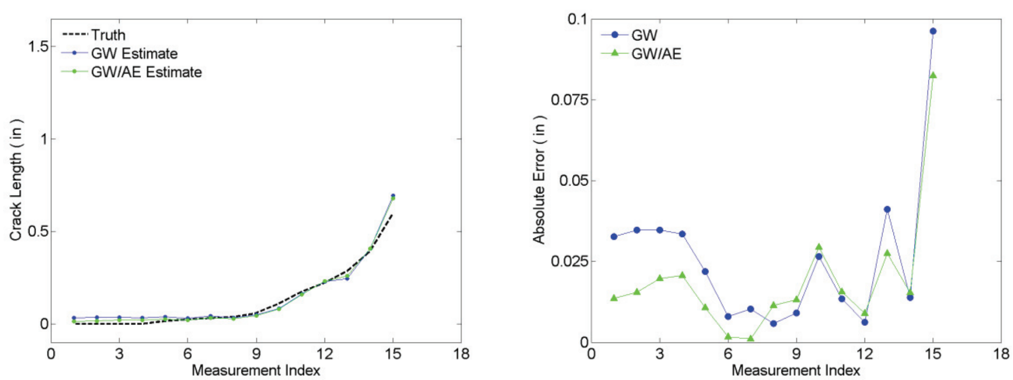
The data from the first (training) coupon includes measurements at 26 different cycle counts, up to 977,500 cycles, during which the crack initiated and grew to a total length of 1.45 in, as shown by the "Truth" data in Figure 2(a). Six features are selected by the stepwise regression procedure and these features are used in a multi-linear regression model for crack length, providing the "GW Estimate" lengths shown in the figure. This algorithm has then been utilized to estimate crack lengths based on the pitch-catch data collected from the second (testing) coupon whose data is not utilized during the algorithm design. At the time of this paper, the crack in the second coupon had only been grown to a total length of 0.6 in. As shown in Figure 3, the algorithm provides reasonably accurate crack length estimates.

A focus of these studies is to investigate data fusion, where both guided wave and AE data are utilized in the SHM process to improve accuracy. Unfortunately, the available hardware precluded useful AE measurements. Efforts are underway to determine alternative measurements techniques to collect usable AE data during testing of the remaining dogbone coupons. To illustrate the potential benefits of data fusion, sets of AE data have been synthesized. The synthesized AE data is assumed to take the form of total number of measured AE events versus crack length, and has been based on similar fatigue testing of a steel specimen [14].



(a) (b)

Figure 2. (a) Actual and estimated crack lengths for training coupon and (b) error in crack length estimates



(a) (b)

Figure 3. (a) Actual and estimated crack lengths for testing coupon and (b) error in crack length estimates

The synthesized AE events data has been utilized as another feature in the pattern recognition algorithm detailed above. This AE-based feature and six features from the guided wave data are again used in the multi-linear regression model for crack length, providing the “GW/AE Estimate” lengths shown in Figures 2 and 3. The guided wave classifier already provides reasonably accurate crack length estimates, but the potential for improved estimates is shown in the figures. It should be noted that any algorithm improvements should not be quantified based solely on the estimated crack lengths. Algorithms from various data fusion techniques should be compared using accepted probability of detection (POD) and false alarm rate.

CONCLUSIONS

PZT transducers are broadband devices that can operate over a large frequency range and can be utilized to collect measurements using multiple sensing modalities. For these studies, fatigue cycling has been performed on aluminum dogbone specimens with PZTs used to provide signals measuring guided waves, AE events, EMI, and strain. Each of these individual sensing techniques could be utilized for crack detection and crack growth estimates using statistical pattern recognition methods. However, the potential exists to improve SHM system performance by using data fusion methods applied to combinations of these sensing techniques. To demonstrate the potential benefits of data fusion, crack detection algorithms have been developed using only guided wave measurements, as well as the combination of guided wave and AE data. Artificial AE data has been utilized since the current testing hardware did not allow for the collection of useful AE data. Future studies will address the collection of AE data and consider data fusion incorporating EMI and/or strain data.

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