Yipei Zhang
Graduate Student
Georgia Institute of Technology
yzhang3432@gatech.edu

Salman Azmi
Graduate Student
Georgia Institute of Technology
sazmi003@gatech.edu

# Predicting Cracks in Aluminum Lap Joints Using Lamb Wave Signals

ISYE 6748: Applied Analytics Practicum

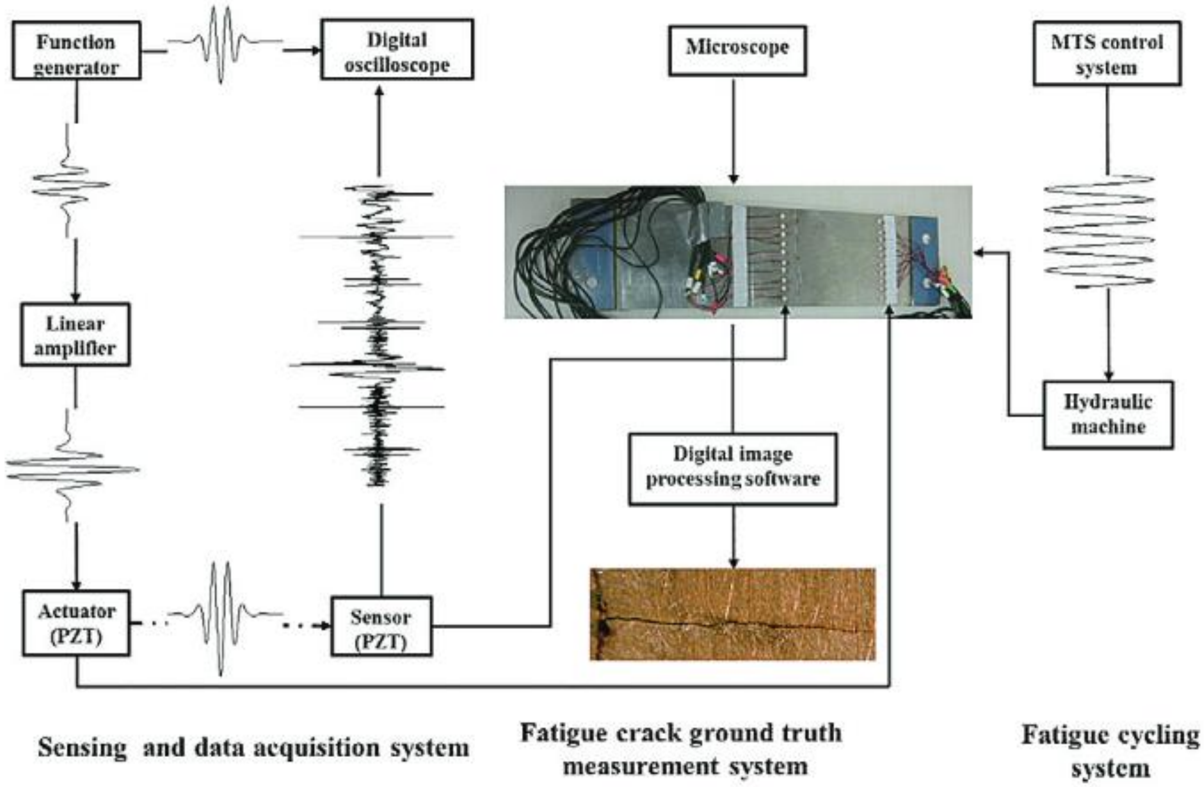
Sponsored by Sandia National Laboratories

## Abstract

This paper introduces a model created to predict the crack length on an aluminum lap joint exposed to Lamb waves generated by piezoelectric (PZT) wafers. We developed, trained, and tested the model against a dataset provided by He et al. (2013) [1], [2] consisting of 6 training and 2 test sample joints. After decomposing our initial dataset, we tested various algorithms, ultimately selecting a support vector machine (SVM) to classify both fixed and variable amplitude data. We validated our models and found them to be highly effective and but concede concerns regarding the size of our dataset.

## Background and Objective

Lap joints refer to two thin pieces (typically sheets) of materials joined together using a partial overlap. Welders can create lap joints with aluminum sheets which are commonly used in the aerospace industry. Despite being structurally weak, lap joints are easy and cheap to manufacture, and are safely used to build fuselages and wings. He et al. (2013) used guided ultrasonic waves to assist in structural health monitoring (SHM) and explains that “Lamb waves are a form of elastic perturbation, which can be used to interrogate the integrity of a target system” [1]. The following image from He et al. (2013) summarizes the experiment they executed to gather the data used in this paper:




Our objective with this paper is to introduce our attempt at implementing a regression model which leverages the supplied data to predict the length of a crack and an illuminant lap joint after it has been exposed to some of quantity of Lamb waves. We will then leverage this regression model by allowing users to supply a threshold of their choice and a data set to determine whether the size of the crack is acceptable or not. By providing a binary classification option, we aim to create a mock scenario in which someone assessing the structural integrity of lap joints (such as an engineer, technician, or material researcher) can preemptively approximate the size of a crack on a joint after an exposure to a known amount of force. Assuming the input quantity is known (or at least approximately known), an engineer or a technician would also be able to leverage a model like this to help preemptively schedule maintenance on a craft or part.

## Data Characterization

Our data consists of 38 training samples voltage drops recorded on 6 different lap joint specimens. Each sample consists of excitation and received signals collected by two sensor-actuator pairs. The length of the crack was recorded at the end of every cycle which consists of 4000 recorded intervals. We are treating each sample as two different inputs for the same crack length. This leaves us with a dataset of 76 crack lengths and 4000 predictors for each length. Our testing data consists of one specimen tested for 4 cycles with fixed amplitude (like our training data) and one specimen tested for 5 cycles with variable amplitude.

## Methods

To improve our model's computational runtime, we simplified our data by decomposing it. For every cycle record, we compressed the data by recording averages in groups of 40, converting a record with 4000 data points into a record with 100 data points. After we took our compressed data, we used it to train various algorithmic models and assessed their performance against our test data. Prior to compression, we also attempted principal component analysis (PCA) but found the results to be unsatisfactory in the end.

In our model selection, we trained 3 models: a linear regressor, an MLP regressor, and an SVM. The linear and MLP regressors were trained on the compressed dataset and original continuous labels whereas the SVM was trained on labels we created using arbitrary classification thresholds.

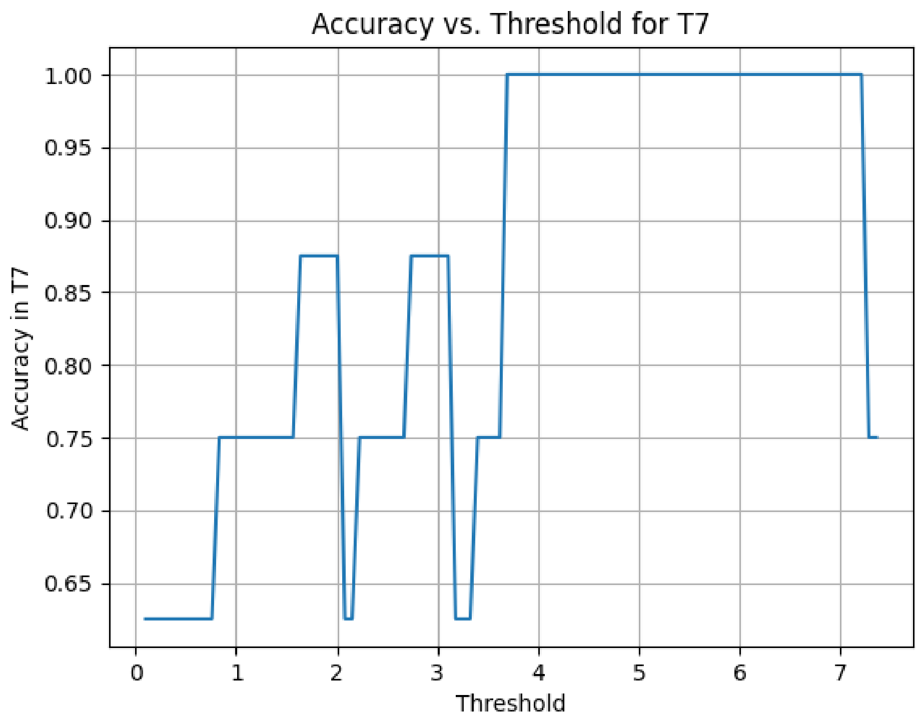
## Results

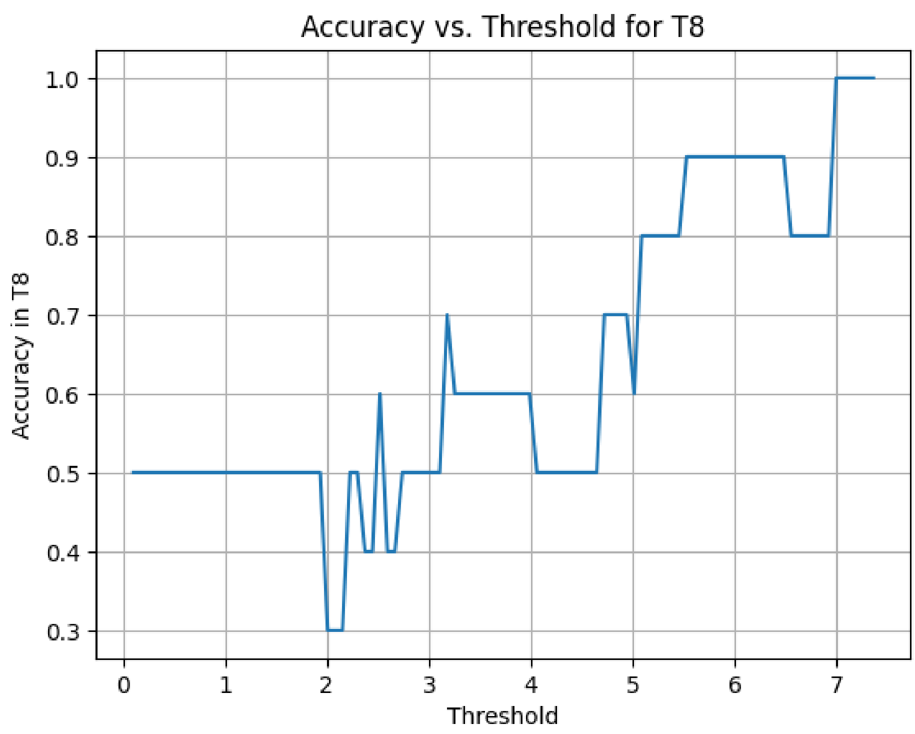
We found that while the MLP regressor performed exceptionally well when testing against the variable amplitude specimen, the SVN performed best when testing against both the fixed and variable amplitude specimens. We decided that instead of creating a classification function with the regressor, we will rely on the SVM classifier.

The following table shows our mean square error (MSE) for both regressors against both fixed (specimen T7) and variable (specimen T8) amplitudes datasets:

| Algorithm | Fixed Amplitude MSE | Variable Amplitude MSE |
| --- | --- | --- |
| Linear Regression | 4.640 | 101.928 |
| MLP Regression | 4.045 | 1.516 |

The following graphs display the recorded accuracies of our SVM classifier for both fixed (specimen T7) and variable (specimen T8) amplitudes:




The following table shows the range of threshold with the best prediction accuracy in SVM for both fixed (specimen T7) and variable (specimen T8) amplitudes datasets:

| | T7 | T8 |
|---|---|---|
| Threshold Range | 3.693 to 7.213 | 6.993 to 7.36 |
| Best Accuracy | 1.0 | 1.0 |

# Discussion

The purpose of this paper is to introduce our attempt to implement a model that can predict cracks in aluminum lap joints using measurements from generated Lamb waves. After testing various algorithmic models, we determined a final model for predicting cracks on lap joints impacted by both fixed and variable amplitudes. Since our SVM is a classifier trained on a specific threshold, we created a classification function to allow users to classify predictions against their sample datasets using a provided threshold input.

One of our earliest and most persistent concerns was the size of our dataset. We tried to generate synthetic data to improve our training and testing, but due to the small size of our initial data, we were unable to do so. As such, our testing sets for both our fixed and variable amplitude specimens are limited to 8 and 10 values, respectively.

In a future iteration of this study, we would like to further research synthetic data generation, re-attempt our approaches with a much larger dataset, and conduct further background research on the durability of aluminum lap joints and the properties of Lamb waves.

# References


1. He J, Guan X, Peng T, Liu Y, Saxena A, Celaya J, Goebel K. **A multi-feature integration method for fatigue crack detection and crack length estimation in riveted lap joints using Lamb waves.** *Smart Materials and Structures*. 2013 Sep 4;22(10):105007.
2. Peng T, He J, Xiang Y, Liu Y, Saxena A, Celaya J, Goebel K. **Probabilistic fatigue damage prognosis of lap joint using Bayesian updating.** *Journal of Intelligent Material Systems and Structures*. 2015 May;26(8):965-79.