Structural Health Monitoring Using Guided Ultrasonic Waves to Detect Damage in Composite Panels

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Introduction

In the aircraft industry safety, maintenance costs, and optimum weight are three of the most important factors to consider in design. Composite materials, such as carbon fiber reinforced polymers (CFRPs), are increasingly used in aerospace applications due to their high strength to weight ratio. However, there are still many challenges to overcome in order to have full confidence in the use of composite structures. Specifically, composites have very different failure types and modes than traditional metal materials used in aircraft. This makes prediction of damage initiation and propagation difficult in practical application.¹

Use of Structural Health Monitoring (SHM) would help to solve this problem. SHM, the process of implementing a damage detection and characterization strategy for engineering structures, enables engineers to assess realtime conditions in a structure. This would allow a condition based maintenance strategy that would increase aircraft safety and decrease maintenance costs by eliminating unnecessary inspections. The essential steps in an SHM system are to first detect the damage, second classify the type of damage, third quantify the damage, and fourth predict damage propagation. This project is geared specifically towards quantification of delamination in composite laminates; a specific type of damage found in this material. Training algorithms with different feature sets and damage size classifications will be compared to find the best strategy for prediction of delamination severity.

Research

The Structures and Composites Laboratory (SACL) at Stanford University is developing an SHM technique based on the propagation of a type of ultrasonic wave, called Lamb waves, through thin-plated structures. The Lamb waves are propagated and sensed via piezoelectric sensor networks, specifically Acellent's SMART Layers®, adhered to the structure. SACL works with laminated CFRPs, which are thin-plated structures constructed of stacked plies with unidirectional carbon fibers bonded by epoxy. The two main types of damage in these composite structures are matrix micro-cracking and inter-laminar delamination. Matrix micro-cracking happens within each ply in the epoxy between carbon fibers, and is a precursor to the more serious damage type of delamination. Delamination is the de-bonding between plies which significantly decreases the strength of the material and leads to ultimate failure in the structure. Current detection methods and research in SACL are geared towards detection of these damage types and quantification of matrix micro-cracking in composite laminates. project will focus on quantification of delamination, specifically prediction of the severity of the delamination, which is directly correlated to damage size.

Experiments

Experiments to study damage propagation in composite panels loaded in tension-tension fatigue are ongoing in SACL in collaboration with NASA Ames. The bonded piezoelectric networks generate ultrasonic signal data to analyze for changes in the structure corresponding to damage. Two sets of six sensors are bonded to the

structure, with one set used as actuators to generate the signal at seven different actuation frequencies (150 - 450 kHz at 50 kHz intervals) and the second set used as sensors to collect signal data. This yields a total of thirtysix diagnostic paths with which to map damage across the coupon (Figure 1). The tension-tension cyclic loading, simulating continued use of a structure, is provided using SACL's MTS machine. After an interval of cycles, dependent on the current point in the lifetime of the coupon, signal data is collected and samples are X-rayed to provide images of the real damage type and quantity. The sensor signals from all paths can be processed with different techniques to extract parameters from both the time and frequency domains to use as features in training algorithms. All sensor data is compared to a baseline, taken before loading the sample as an example of a healthy system. Coupons are tested to failure.

Data

For each cycle interval, the data from all thirty-six paths are used to create a complete "map" corresponding to the current state of the structure, for which the actual delamination width and height are measured from the Xray (Figure 2). For this project, five different features were chosen and computed from the raw experimental data: time of flight, amplitude change, 1-p (correlation coefficient between the baseline and new waveform), the power spectral density (PSD) overall maximum value, and the maximum PSD value at the actuation frequency. The PSD of a signal describes how the power of that signal is distributed with frequency. Each extracted parameter was normalized with its corresponding value from the baseline signal. Previous work in SACL has shown the actuation frequency of 250 kHz to yield the best modeling results, so at this stage only that frequency data was used.

Classification Algorithm

In classification, I attempted to classify the delamination in a composite panel as fitting into one of multiple different severity classes, which are dependent on size. This would correspond in application to declaring a known damage as either "minimal", "acceptable", or "critical" with respect to the desired function. Engineering

analysis would be used to determine the acceptable limits for existing damage in a structure, with an appropriate safety factor. Therefore I modeled the data as a multinomial problem using softmax regression, a generalization of logistic regression that allows for more than two class labels.

Two types of class labels were used for the classification, both categorized by the above mentioned damage criteria. The first was an approximation of the area of the delamination from the height and width measurements. The second was the fraction of the vertical distance between sensors (see Figure 2) that the height of the delamination was at each interval. In application, these thresholds would be chosen from physics-based models that determine the amount of damage allowed before maintenance is required.

The softmax regression algorithm I wrote is derived from the lecture notes and UFLDL online tutorial. I implemented a weight decay term λ as suggested in [3] to guarantee a strictly convex cost function and unique solution, yielding the following cost function $J(\theta)$ and its derivative.

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^{m} \sum_{j=1}^{k} 1\{y^{(i)} = j\} \log \frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k} e^{\theta_l^T x^{(i)}}} \right] + \frac{\lambda}{2} \sum_{i=1}^{k} \sum_{j=0}^{n} \theta_{ij}$$
(1)

$$\nabla_{\theta_{j}} J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} \left[x^{(i)} \left(1\{y^{(i)} = j\} - p(y^{(i)} = j | x^{(i)}; \theta) \right) \right] + \lambda \theta_{i}$$
(2)

I then used gradient descent to update $J(\boldsymbol{\theta})$ until convergence.

In training the model I used leave-one-out cross validation $(LOOCV)^4$ iterating through all training examples, as I have relatively little data to work with. The generalization error of the model was estimated by tabulating the number of incorrect predications over all LOOCV cases and dividing by the total number of training examples. Tables 1-2 in the Appendix show the generalization error for different combinations of

threshold values for the classes. The best achieved error of a case where all classes were actually predicted was 19.18%. When varying the thresholds, certain classes were harder for the algorithm to predict, i.e. the model would predict most samples as being from the largest damage class and not predict any in the middle damage-size class. No combination of threshold values yielded good prediction in all three classes (Figures 3 – 5). I believe this results from having more data for the large damage case, as delamination grows quickly and non-linearly with continued fatigue. Therefore it is more difficult experimentally to capture the early delamination stages with intermediate sizes.

Feature Selection

I wrote a forward search algorithm to attempt to refine my number of features and achieve a more accurate "map" of the delamination without noise from features not contributing to the prediction. Because forward search is computationally expensive, I wrote a hold-out cross validation algorithm to select features, where the data set was randomly separated into 70% training data and 30% test data. Once the final feature set was selected, I used LOOCV to estimate the error for the new model with the reduced feature set. I found that my algorithm selected a very limited number of features, and therefore ended up increasing the error in the final implementation of softmax regression.

Additionally, I attempted using only signal paths directly adjacent to the damage area in order to reduce the feature set. This reduced the number of paths from to nine (see Figure 2). Again, this increased the test error.

Logistic Regression

Finally, I regressed the softmax algorithm into logistic regression by only using one threshold value. I did this because the softmax algorithm was doing relatively well at recognizing two out of three classes, so I decided to attempt using it as a binary classifier. Using the algorithm as an indicator of delamination size greater than some minimum acceptable value worked very effectively, with the lowest achieved error value of 5.479%. The error values are shown in Table 3 and a sample plot in Figure 6.

Conclusions and Future Work

The softmax regression algorithm works moderately well as a multi-level classification of damage size. Logistic regression is very effective at indicating delamination size above a given threshold. The most difficulty in the softmax regression algorithm comes from the skew of the data towards larger delamination size.

Refinement of the threshold values for the different softmax classes may help minimize error in the algorithm. A method is needed to systematically test different classes and converge on the optimal threshold values, which hopefully would coincide with physics-based damage thresholds. Moreover, this classification may work better with different algorithms and machine learning strategies. Therefore a next step would be to apply this data to other algorithms and study their effectiveness. This work only utilized one actuation frequency of sensor data in the training set, and this could be expanded to use the other six available frequencies to yield more results. SACL also has additional composite panels of different layups and material properties that could be added to this study to see whether the predictive algorithm dependant on laminate configuration.

Acknowledgments

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References

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- [3] "Softmax Regression," *UFLDL Tutorial*, http://deeplearning.stanford.edu/wiki/index.php/Softmax regression, accessed 15 Nov 2012.
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Figure 1 – Illustration of wave propagation along a single path of thirty-six available, along which we can measure signal



Figure 2 – An example of delamination (area outlined in white in the left of the coupon) formed in a test sample after 80,000 cycles. Height and width of delamination are measured to determine severity.

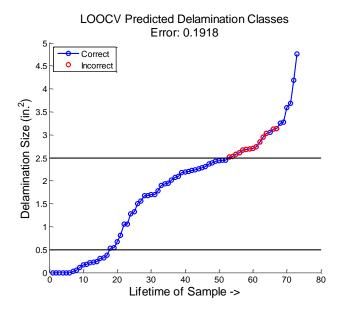


Figure 3 – Softmax classification based on damage area with class thresholds 0.5 in.² and 2.5 in.², which does not effectively capture the change between classes 2 and 3.

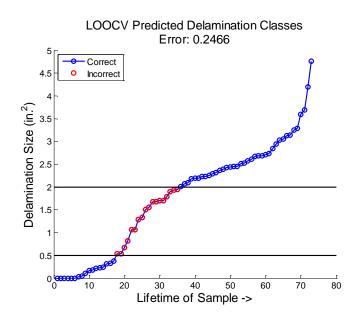


Figure 4 – Classification based on damage area with class thresholds 0.5 in.² and 2 in.², which does not effectively capture class 2 (the mid-range damage area).

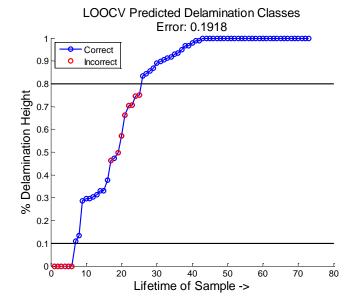


Figure 5 – Classification based delamination height percent with class thresholds 10% and 80%, which does not effectively capture class 1 (the low damage area) or the upper half of class 2 (the mid-range damage area).

Error: 0.05479 Correct Incorrect Delamination Size (in.²) 3.5 3 2.5 2 1.5 20 40 60 10 30 50 70 80 Lifetime of Sample ->

LOOCV Predicted Delamination Classes

Figure 6 – Binary classification based on damage area with a threshold at 0.75 in.², which effectively predicts damage area above the chosen area.

Appendix B - Tables

Lower bound refers to the threshold between the first and second class ("small" and "medium" size delamination), and the upper bound refers to the threshold between the second and third class ("medium" and "large" size delamination).

Table 1 – Generalization errors for models with varying delamination area thresholds.

Area (in.²)		Upper Bound				
		2	2.25	2.5	2.75	
Lower bound	0.5	0.2466	0.2603	0.1918	0.1644	
	0.75	0.2466	0.3425	0.2466	0.2466	
	1	0.2466	0.3288	0.2603	0.2192	

Table 2 – Generalization errors for models with varying height fraction thresholds.

Height Fraction		Upper Bound				
		0.75	0.8	0.85	0.9	
	0.1	0.1781	0.1918	0.2192	0.2329	
Lower Bound	0.15	0.2192	0.2329	0.2466	0.3014	
	0.2	0.2192	0.2329	0.2466	0.3014	
	0.25	0.2192	0.2329	0.2466	0.3014	