46th Annual Review of Progress
in Quantitative Nondestructive Evaluation
QNDE2019
July 14-19, 2019, Portland, OR, USA

QNDE2019-1234

DATA FUSION APPROACH FOR ULTRASONIC AND X-RAY COMPUTED TOMOGRAPHY DATA

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ABSTRACT

Quantitative characterization of impact damage in polymer matrix composite panels is desired to inform the initial conditions of damage evolution models for subsequent mechanical loading. Previous work from the authors focused on predicting X-ray Computed Tomography data from Ultrasonic Testing data to produce a 3D representation of the damage. The predicted damage with this approach contained artifacts near matrix cracks, the tips of delaminations, and damage occluded by the topmost delaminations. In this work, a data fusion approach is developed to segment the damage using both sets of data directly. This 'data fusion' approach involves the training of a classifier using both UT and XCT data as inputs and predicting damage/no damage as the output. Details of the model and data processing are described, along with the resulting segmentation.

Keywords: Data Fusion, Ultrasound, X-ray Computed Tomography

NOMENCLATURE

PMCs	Polymer Matrix Composites
BVID	Barely-Visible Impact Damage
XCT	X-ray Computed Tomography
UT	Ultrasonic Testing

1. INTRODUCTION

Polymer-matrix composites (PMCs) subject to impact events may contain barely-visible impact damage (BVID). This presents challenges to the lifecycle management of composite structures. Improved 3D characterization of damage can enable accurate modelling of damage evolution [1,2], a requirement for implementing a damage tolerance approach for PMCs [1]. X-ray Computed Tomography (XCT) can produce 3D characterizations of damage, but imaging constraints can limit contrast and resolution and prevent characterization of small damage features. Ultrasonic testing (UT) in normal-incidence inspections can provide high depth resolution, but some features are not resolved because they are occluded by features at a shallower depth. Several recent efforts [3-5] investigated the use of oblique angle incidence UT inspection data for 3D damage characterization. Prior work by the authors [6] described the use of supervised learning to predict XCT data from UT data. The approach produced 3D damage that contained some of the aspects of both UT and XCT data, including improved ability to resolve the presence of delaminations farther from the impact site that were too thin for XCT alone to characterize. However, the approach also produced many undesirable artifacts in the predicted damage, including noise at the tips of delaminations, noise at the locations of matrix cracks, and non-physical predictions of delaminations in lower regions occluded by upper delaminations, as seen in Figure 1.

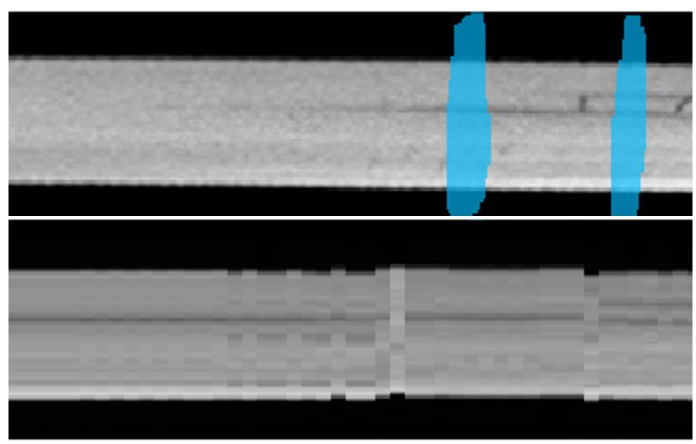

FIGURE 1: COMPARISON OF ACTUAL (ABOVE) AND PREDICTED XCT DATA FROM UT DATA (BELOW) [6]

This work describes a new approach for characterization of BVID that uses both XCT and UT data with modern data fusion methods.

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2. MATERIALS AND METHODS

The polymer matrix composite (PMC) panel under study was a 24-ply layup of IM7 carbon fiber 977-3 polymer matrix plies. The plies were stacked according to the sequence [-$45_3/90_3/45_3/0_3]_s$. The dimensions of the panel are 101.7 mm x 152.5 mm x 3.245 mm (4” x 6” x 1/8”). The panel was subjected to a drop tower impact test at 10 J, resulting in barely visible impact damage (BVID).

2.1 X-ray Computed Tomography of PMC BVID

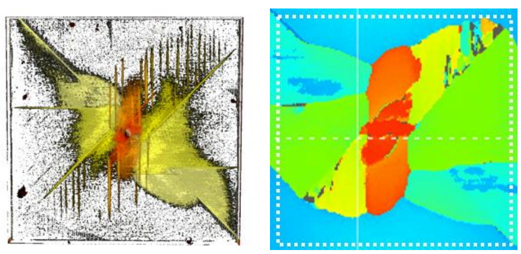
The BVID was characterized with XCT with details found in [6]. This resulting reconstruction is 68.2 mm on each side, with a voxel length of 66.7 µm.

2.2 Ultrasonic Testing of PMC BVID

The damage was also characterized with normal incidence pulse-echo UT in an ultrasonic inspection system, with details according to [6]. The resulting UT data set was 154 mm x 102.4 mm x 20 µs, with a spatial resolution of 0.4 mm and time resolution of 0.01 µs.

2.3 Comparison of the Data

Segmentation of the damage with a classifier at the voxel level for the XCT data is shown in Figure 2 along with a time-of-flight (TOF) C-scan from the UT data for the same region of the panel.



XCT UT

FIGURE 2: COMPARISON OF SEGMENTED XCT DATA AND TOF UT DATA

It is readily observed that the segmented XCT data contains delaminations and matrix cracks throughout the volume of the panel. Also, the UT data captures more of the extent of the delaminations than the segmented XCT data. This is because near the outer edges of the damage, the delaminations become thinner than the XCT system is capable of resolving. However the UT data is missing other 3D information about the presence of matrix cracks and hidden delaminations. Neither modality captures the full extent of the damage.

2.4 Data Fusion for XCT and UT Damage Characterization

Key to advanced data fusion is the concept of ‘diversity’ [7] within the data. Diversity refers to parts of the data providing ‘unique’ information not present in other parts of the data. The spatially-registered XCT and UT data is an example of multimodal data and contains diversity. There are many approaches to data fusion, including *data integration*, *processing modalities sequentially*, and *true fusion* [7]. An example of *data integration* would be developing a classifier for each modality and applying some decision strategy to the output of each classifier to determine a final class for each voxel. An example of *processing modalities sequentially* involves using one data set to constrain a classifier applied to the other data – this approach was used in [6]. The data fusion approach used in this work is *true fusion*, specifically *true fusion using multivariate features*. The *true fusion* approach amounts to using features from multiple modalities as inputs to a single classifier.

As depicted in Figure 3, the true fusion method involves extracting features from both the UT and XCT data, some of the voxels are labeled, and they are used train a kernel classifier (an extension of kernel regression [8-9] for classification) to segment the damage in the remaining voxels.

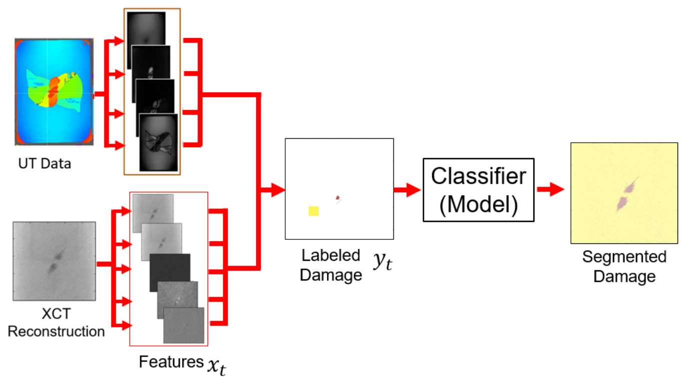


FIGURE 3: TRUE FUSION APPROACH FOR SEGMENTATION

The features extracted can include the raw data, local means, medians, variances, and higher order features such as edges, shapes, gradients, etc. through the use of convolving various filters of different sizes, shapes, and types (such as Sobel, Laplacian, etc.). Others include gated time of flight and max amplitude. These will be explored and discussed in the associated presentation.

The proposed approach is an example of supervised learning [10] that is similar to but distinct from that used in [6] which involved a sequential processing of the modalities. Once the damage has been segmented, further quantitative characterization of sizes, shapes, and statistics of damage can be carried out [6,11].

3. RESULTS AND DISCUSSION

The new classifier and resulting segmentation of the damage will be presented at the conference. An example of the segmented damage using the sequential data fusion approach in the previous work is presented in Figure 4.

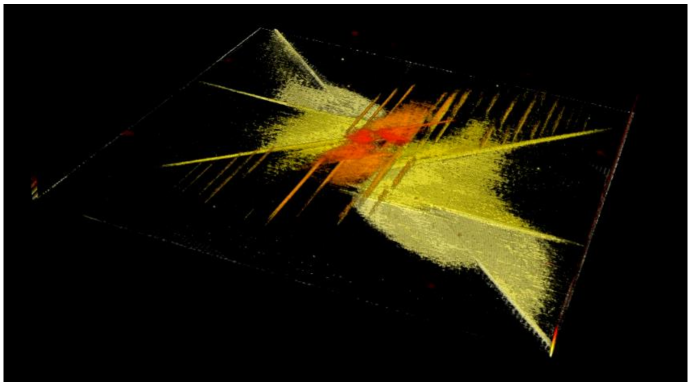


FIGURE 4: SEGMENTED DAMAGE USING DATA FUSION APPROACH

4. CONCLUSION

In this work, we demonstrated the use of modern data fusion methods for X-ray Computed Tomography data and Ultrasonic Testing data. A classifier was developed using features extracted from XCT and UT data as inputs, and predicting as output whether each voxel was air, damage, or undamaged PMC. We anticipate the segmented damage using these techniques to be a significant improvement over the previous results in [6], because rather than using one modality to constrain the results of another modality, we are using both NDE modalities in a manner in which they can interact to better inform the decision for each voxel.

ACKNOWLEDGEMENTS

Portions of this work are funded by the U.S. Air Force through contracts FA8650-14-D-5224 TO 0001 & TO 0002. The impact tests performed by Sarah Wallentine (AFRL) and Norm Schehl (UDRI) and the collection of the ultrasound data by David Zainey (UDRI) is acknowledged. DISTRIBUTION STATEMENT A. Approved for public release; distribution is unlimited. Case Number 88ABW-2019-1310.

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