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Nondestructive evaluation (NDE) involves studying the properties of a material without causing damage to the material

- A basic example of NDE is a doctor using an x-ray to determine if a patient has a broken bone
- At NASA, NDE researchers are evaluating Computed Tomography (CT) scans in order to identify anomalies for improving and developing materials for stronger, lighter, and safer structures

Current analysis of CT scans of materials:

- Is a time-consuming process
- Requires significant subject matter expertise
- Has only minimal automation

Automated Algorithms:

- Will help SMEs to design better material compositions and structures
- Will help SMEs with innovative composite additive manufacturing using ISAAC
Outline

• Overview and Goals

• Statistical Algorithmic Techniques
  – Cross Hatch Regression
  – 2 Dimensional Regression
  – SME Validation Methodology

• Machine Learning Algorithmic Technique
  – Deep Learning – Convolutional Neural Networks
Nondestructive Evaluation (NDE)

• Inspect material for defects without causing changes (Doctor using x-ray)

• Techniques being used
  – Ultrasound
  – Thermography
  – X-ray computed tomography (CT)
    • This anomaly detection work now focuses on CT data
Objectives for “Big Data” in NDE

• Large volumes of data are collected (typically 2 GB and larger in a 4 hour time period)

• Currently procedure for reviewing data is displaying data on computer monitor and subject matter expert identities anomalies in data

• This can require examining as many as thousands of images or even regions of thousands of images to ensure all anomalies are detected

• It is desirable to develop methodologies to:
  • Reduce the amount of data that needs to be reviewed by a human
  • Identify subtle variations that are difficult for a human to detect due to low signal to noise ratios
  • Identify features more easily recognizable in three dimensions
Anomaly Detection in the Nondestructive Evaluation of Materials (NDE)

Develop Techniques and algorithms to automatically detect various kinds of delaminations in CT scans from nondestructive evaluations of materials.

**Goals**

1. Accurately identify and characterize anomalies in various materials and significantly reduce SME analysis time

2. Discover additional anomalies that were previously undetected by visual analysis of an image

3. Enable SMEs to design better material compositions and structures

4. Help SMEs with innovative composite additive manufacturing using ISAAC
X-ray Computed Tomography (CT)

- Specimen rotated on turntable
- 2-D “shadowgraphs” at multiple angles recorded
  - Intensity proportional to sum of densities along path through material
- 3-D structure reconstructed from 2-D shadowgraphs
Example of CT Data: Defects in Carbon Fiber

Delamination

- **Current Analysis**
  - Manually done by expert
  - Time consuming
  - Requires significant expertise

- **Objective**
  - Develop tools to automate analysis
Algorithmic Techniques Being Developed

<table>
<thead>
<tr>
<th>Technique</th>
<th>Data Analytics and Machine Intelligence Team Member</th>
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<tbody>
<tr>
<td>Crosshatch Regression (Statistical Algorithm)</td>
<td>Colin Lockard (CS Masters Student)</td>
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<tr>
<td>Two-Dimensional Regression (Statistical Algorithm)</td>
<td>Lin Chen (Software Developer)/Ray McCollum (Statistician)</td>
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<tr>
<td>Convolutional Neural Networks (Machine Learning)</td>
<td>Daniel Sammons (CS Masters Student)</td>
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</table>
1. Divide image into series of x- and y-signals
2. Fit linear model to each signal with robust regression
3. Identify outliers against fitted model
4. Confirm delaminations using random forest algorithm
## Results of Crosshatch Regression on Simulation Data

### Simulated Data

![Images of simulated data with crosshatches](image)

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Crosshatch Regression Results on Experimental Data

- Good results overall
- Could be a few false positives
- SME validation will help
Key Findings and Next Steps for Crosshatch Regression

• Results are good on both simulated and experimental data

• Advantages
  – Accurately segment delaminations in carbon fiber CT
  – Ability to find anomalies in data

• Challenges
  – May have trouble generalizing to other defects/materials/modalities

• Next Steps:
  – Validation by SMEs with more experimental data sets using GUI
  – Targeted use for structural analysis of materials in near future
Two-Dimensional Regression Algorithm

1. Smooth
2. Fit the pixels in a slice into a 2D regression function
3. Replace the pixel value by residual value, which is (regression value – pixel value)
4. Identify the anomaly pixels by histogram plot

If a residual value is out of family, the pixel is a delamination pixel

If residual > m + kσ, this pixels is anomaly pixel, in which m is the mean of the pixel residuals, σ is the std of the pixel residuals, k is a threshold parameter
# Results of Two-Dimensional Regression

<table>
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**Simulated Data**

**Real Data**
Two-Dimensional Regression – Results on experimental data
- Overall good results
- Could be a few false positives
- SME validation can help
Key Findings for Two-Dimensional Regression

• Results are good on both simulated and experimental data

• Advantages
  – Accurately segment delaminations in CT images
  – Very efficient algorithm

• Challenges
  – May have trouble generalizing to other defects/materials/modalities

• Next Steps:
  – Validation by SMEs with more real experimental data sets using GUI
  – Targeted use for structural analysis of materials in near future
SME Validation of the Two Statistical Algorithms

• So far...
  – Quantitatively validated using simulated data set
  – Passed the “look test” for real data

• Goal
  – Quantitatively validate with real experimental data sets
Validation Methodology

• Segment real data anomalies using pseudo-manual “Chan-Vese” segmentation algorithm

• Validate segmentations with SMEs

• Compare output of automated algorithms with validated segmentations and develop metrics for evaluation
Validation Methodology

Real Data → Segment with Chan-Vese¹ → Segmented Data


Validate with SME
Validation Methodology Cont...

SME Validated Segmented Data

Output from automated segmentation

Compute Metrics (Global TP/FP, RMSD, Hausdorff, etc.)
MATLAB® GUI for Validation

1. Plugin the algorithms into a MATLAB® GUI
2. SMEs are able to preview, change the parameters, test samples by clicking the mouse with the GUI
3. SMEs can use their expertise to validate the algorithms
Convolutional Neural Networks (CNNs)

- CNNS are state of the art for image recognition task
- Based on Deep Learning techniques (advanced neural networks)
- Have a great potential for NDE challenge across materials and modalities

Successful Application of CNNs to Segment and Detect Objects in Medical Imagery

**Neuronal Membrane Segmentation (IDSIA)**


**Mitosis Detection (IDSIA)**

Applying CNNs to NDE

- Highly non-linear model that **learns** features
- Alternating layers of **convolution** with learned kernel and **max pooling**
- Reduce input to 1-D vector (learned feature-vector) which is classified with a neural network
- Trained **patchwise** for segmentation
CNN Results on Simulated Test Set

<table>
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<tr>
<th>Intensity</th>
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<td>81.60%</td>
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<tr>
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<td>89.17%</td>
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<tr>
<td>Missed ROIs</td>
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<tr>
<td>False Positive ROIs</td>
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<td>13.19%</td>
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Results of CNN Analysis on Real Data
CNN Key Findings and Future Work

• **Advantages**
  - Identifies large number of defects with relatively few false positives
  - Ability to adapt to other defects/materials/modalities simply by changing training set

• **Challenges**
  - Struggles to correctly shape larger and smaller defects
  - Using more context to predict each pixel beneficial but using larger windows is computationally prohibitive

• **Future Work**
  - Multi-scale architectures would allow for more context without extra computational burden
  - Use CNN like an auto-encoder for anomaly detection
  - Consultation with ODU Professor with Deep Learning Expertise