Characterizing the Quality of 3D Printed Parts using Deep Learning

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Statement of the Problem

- During the additive manufacturing process, there is a risk of **defects** arising in printed parts
  - **Porosity** – the presence of void space inside the part body; weakens the part
- We would like to **detect** defects such as these before printing is finished, so we can dynamically correct them
The Data

- An Optomex LENS 750 system was equipped with a pyrometer aimed at the melt pool, and an infrared camera in the print chamber.
- The system printed a thin wall out of Ti-6Al-4V.
- The pyrometer and IR camera feeds were captured as pixel value matrices at each time step.
Examples

Pyrometer

IR
My Approach

- Use a **neural network**: layered graph representing a series of operations converting input data (pixels) to output data (class)

- Neural networks need to **learn**: given labeled training data, compute error at each step and auto-update weights and edges
My Approach

✧ Combine two types of neural network:
  ✧ **Convolutional**: Consolidates spatial data into “features”
  ✧ **Recurrent**: Input is given in an ordered sequence

✧ Because there are two distinct types of data, make two neural nets – PyroNet and IRNet – and compare their outputs
PyroNet - Overview

- Input: Critical region of a pyrometer capture (a 69x120 .csv file)
- PyroNet is **not recurrent** because there is minimal time dependency between successive pyrometer images
- Testing accuracy is **very high** – reliably 94%
PyroNet - Data Preprocessing

- Read .csv files into matrices, pair them with class
- Dataset: 1,492 successes, 71 failures…?
  - Success/Failure Ratio: 21:1
- Because the dataset does not have a lot of failures, the neural net cannot train effectively
- We also cannot get new data…
  - …because the system is in Mississippi.
PyroNet - Data Preprocessing

✧ Solution: create **artificial failures** using a process called **data augmentation**
  ✧ Take the existing images of failures and **slightly transform them** – now we have more failures!

✧ Dataset: 1,492 successes, 71 failures, **700 augmented failures**
  ✧ Ratio: **2:1**
Terminology

- **Conv2D**: Layer that applies a 2D convolution to the image
- **MaxPool2D**: Layer that reduces the size of its input by representing a whole area by the maximum value in that area

![Image of Conv2D and MaxPool2D examples]

- Image
- Convolved Feature
- Max Pool

Max-Pool with a 2 by 2 filter and stride 2.
Terminology

- **ReLU**: Rectified Linear Unit – maps any negative values to 0, making the entire network nonlinear.

- **CMR cell**: Conv2D $\rightarrow$ MaxPool2D $\rightarrow$ ReLU, in order.
PyroNet - Structure

Input (.csv file) → CMR cell → CMR cell → Flatten → Dense → Dense → Output (class)
PyroNet - Metrics

Confusion Matrix (453 samples)

<table>
<thead>
<tr>
<th></th>
<th>Actual Non-Pore</th>
<th>Actual Pore</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Non-Pore</td>
<td>297</td>
<td>2</td>
</tr>
<tr>
<td>Predicted Pore</td>
<td>23</td>
<td>131</td>
</tr>
</tbody>
</table>

Training Loss and Accuracy on Pyrometer Data
IRNet - Overview

- Input: 3 subsequent frames of critical region of an IR capture (a 30x120 .csv file)
- IRNet is recurrent because there is spatial information that is changing with time
- Testing accuracy is roughly 90% - looking to optimize further
IRNet - Data Preprocessing

- Read .csv files into sequences of matrices, pair them with class
- Dataset: 5,392 successes, 285 failures, 3,300 augmented failures
  - Success/Failure Ratio: 3:2
Terminology

- **LSTM**: Long Short-Term Memory – layer that maintains information across a sequence of inputs for use in calculation
- **R-CMR cell**: A CMR cell that processes a sequence of inputs to produce a sequence of outputs
IRNet - Structure

Input
(3 .csv files)

R-CMR cell → R-CMR cell → R-Flatten → LSTM → Dense

Output (class)
IRNet - Metrics

Confusion Matrix (1911 samples)

<table>
<thead>
<tr>
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<th>Pore</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Non-Pore</td>
<td>1021</td>
<td>57</td>
</tr>
<tr>
<td>Predicted Pore</td>
<td>129</td>
<td>704</td>
</tr>
</tbody>
</table>
Potential

- The neural nets have the ability to **quickly recognize patterns that could form pores**
  - Pursue **increased accuracy**
  - Test neural net on **other structures** besides the thin wall
  - Expand neural net to **predict more types of defects**
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