Machine Learning For Etch-Pit Identification for MoEDAL

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MoEDAL

MoEDAL = The Monopole & Exotics Detector at the LHC

Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Nuclear track detectors and aluminium trapping detectors
Nuclear Track Detectors

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Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Highly ionising particles passing through the NTD cause microscopic damage to the polymer that can be reveal with etching
Nuclear Track Detectors

MoEDAL = The Monopole & Exotics Detector at the LHC

Highly ionising particles passing through the NTD cause microscopic damage to the polymer that can be revealed with etching.
Nuclear Track Detectors

Expected SM particles will typically range-in / range-out in one or two sheets.

Heavily ionising particles such as monopoles will cause damage all the way through.
Nuclear Track Detectors

~1 mm² image of an NTD exposed to heavy ion beam to simulate exotic particle signature

Backlit illumination

Etch-pits reflect light away from the camera and appear as black circles

Blurred blobs are etch-pits on the reverse side of the clear plastic NTD – distance between them comes from the angle of incidence of the beam
Nuclear Track Detectors

~1 mm² image of an NTD exposed to heavy ion beam to simulate exotic particle signature

Brightfield illumination

Etch-pits reflect light away from the camera and appear as black circles

Blurred blobs are etch-pits on the reverse side of the clear plastic NTD – distance between them comes from the angle of incidence of the beam

Similar image for NTD exposed to the radiation environment around the LHC interaction point at IP:8
The Challenge...

10s of m² of plastic to be scanned for etch pits

Humans are very good at spotting etch-pits but the process is labour intensive and time consuming

Can Machine Learning techniques be used to train a model that can predict etch-pit locations from scanned images?

This can be used to select interesting candidates for further inspection by a human
Data Sets

Five NTD foils exposed to Pb ion test beam
Front foil exposed at MoEDAL, + LHC bkg
Can Identify etch-pits in unexposed foil trivially
Can map locations between exposed and unexposed foils providing a source of good labels

etch pits can be parametrised by quality eg, how many foils did the ion pass through: maintaining sensitivity to weaker ionisation /
Data Sets - illumination

- Backlit
- Dark field
- Rotational
Alignment

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Can Identify etch-pits in unexposed foil trivially
Can map locations between exposed and unexposed foils providing a source of good labels

3 Alignment holes drilled through the stack to provide a way to realign them after etching
Aligning roughly by hand by overlaying the images gives sufficient resolution – 5 or 6 pixels
Method 1: Sequential deconvolution and convolution followed by ANN

- **Step 1**
  - **Mask selection** using a suitable etch-pit (maximum area, nearly circular) from the image containing multiple etch-pits
  - **Deconvolution** of a new gaussian mask with the entire image
  - **Convolution** of the circular mask with the entire image which generates convolution peaks at the centre of each symmetric etch-pit (value of the peak depends on their common area)
  - **Manual threshold** for separation of etch-pits from noises

- **Step 2**
  - **Artificial neural network** used with two inputs – average of the image generated after deconv-conv and threshold values
  - **Predicted threshold as output** obtained after training which later applied to all other test images
  - **Marking** the actual etch-pits using morphological technique
Method 1: Sequential deconvolution and convolution followed by ANN

1. Real track image and choice of the inverse laplacian of gaussian (ILoG) as mask

   A real track
   Surface plot of the track
   ILoG
   Input layer
   Hidden layer (one)
   Output layer
   Maximum of deconv-conv pattern
   Predicted threshold

2. Mesh-plot after deconvolution with gaussian and convolution with ILoG

3. 1D plot of the above shows higher peak due to deconv-conv with the same mask

4. ANN in Feed-forward architecture for threshold prediction from multiple images

Works on whole single channel backlit images

ANN used to provide thresholding – can be done by hand but is labour intensive

Trained using hand labelled data

Method 2: Fully convolutional networks with transfer learning

**Step 1: CNN Classifiers**

- 4 Convolution + pooling layers
  - 4x4 kernel**
- 2 dense layers combine conv features into output score

Train on 28x28 pixel images with and without etch pits with 5-folding

**Step 2: ~Fully convolutional step**

Use training from 28x28 pixel CNN classifiers but can be applied to any size image

**Step 3: Apply threshold and build segmentation map, etch-pit candidates are then in the middle of “hot-spots”**

Combine CNNs from 5-fold + three lighting scenarios (backlit – 1 channel, darkfield – 1 channel, rotational 8-channels)
Method 3: Fully convolutional networks with U-Net architecture

Provides a method for image segmentation

Method 3: Fully convolutional networks with U-Net architecture

Train on a set of images with and without LHC background – full foil images with 9 channels
Preliminary Results

CNN Classifiers

Performance evaluated on half of the data set kept aside for this purpose.

Use spatial matching between “clean” and “exposed” sheets to measure FP and FN rates.
## Preliminary Results

Performance evaluated on half of the data set kept aside for this purpose

Use spatial matching between “clean” and “exposed” sheets to measure FP and FN rates

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<th>DCC</th>
<th>FCN (Simple)</th>
<th>FCN (Comb.)</th>
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<tr>
<td>True positives</td>
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<td>(Missed detections)</td>
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<td>Total predicted</td>
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## Outlook

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Machine Learning techniques used to successfully identify etch pits

**Work in progress:**
- Still working on harmonising the methods
- Comparison of which candidates are misidentified by each algorithm
- Evaluate the impact of the surface
- Paper in preparation

**Future Work**
- Run with automated scanning of images – could use candidate identification to do adaptive scanning – speed up the scanning process