Automated Visual Inspection of Silicon Strip Sensors

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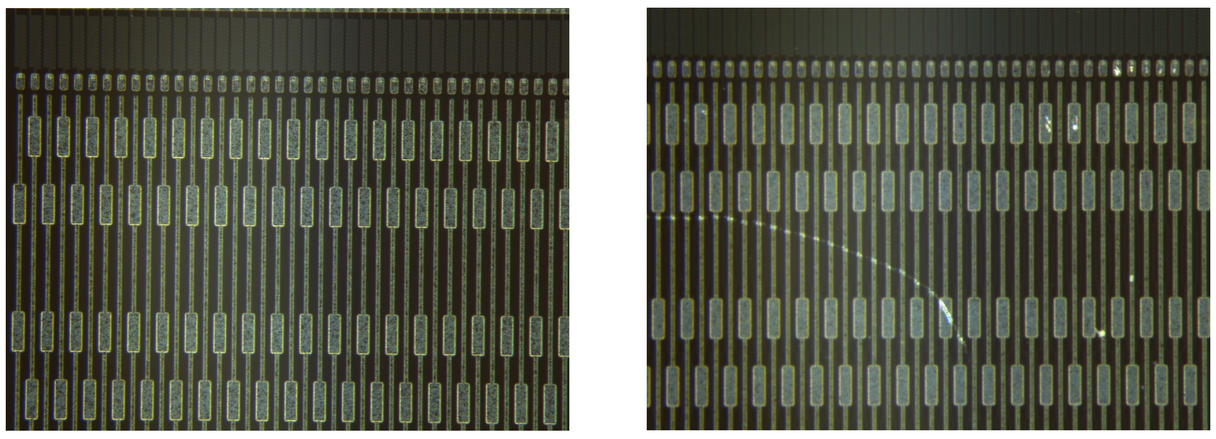
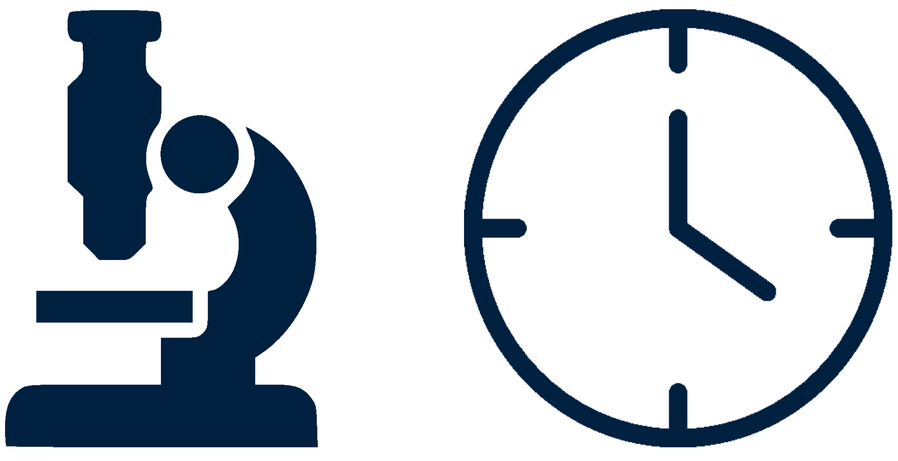
Problem: Identify surface defects on silicon strip sensors



Old Method: Manually scan the surface using a microscope



Issues: Time consuming, tedious, likely inconsistent

Solution: Algorithm to automatically detect defective regions in images

Approaches:

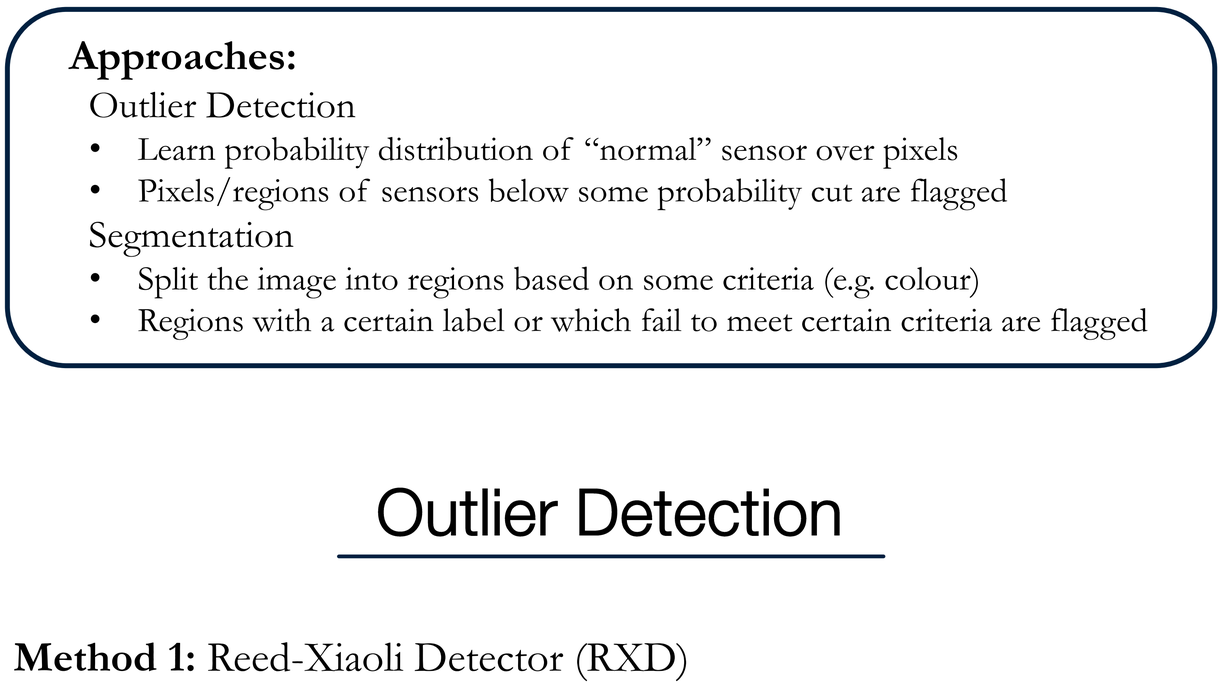
Outlier Detection
- Learn probability distribution of "normal" sensor over pixels
- Pixels/regions of sensors below some probability cut are flagged

Segmentation
- Split the image into regions based on some criteria (e.g. colour)
- Regions with a certain label or which fail to meet certain criteria are flagged

Outlier Detection

Method 1: Reed-Xiaoli Detector (RXD)

- Each pixel in the image $\mathbf{x}$ follows the same multivariate Gaussian
- Calculate sample mean $\hat{\mu}$ and covariance $\hat{C}$ of colours (RGB)
- Negative loglikelihood gives distance metric $\delta(\mathbf{x}) = (\mathbf{x} - \hat{\mu})^T \hat{C}^{-1} (\mathbf{x} - \hat{\mu})$

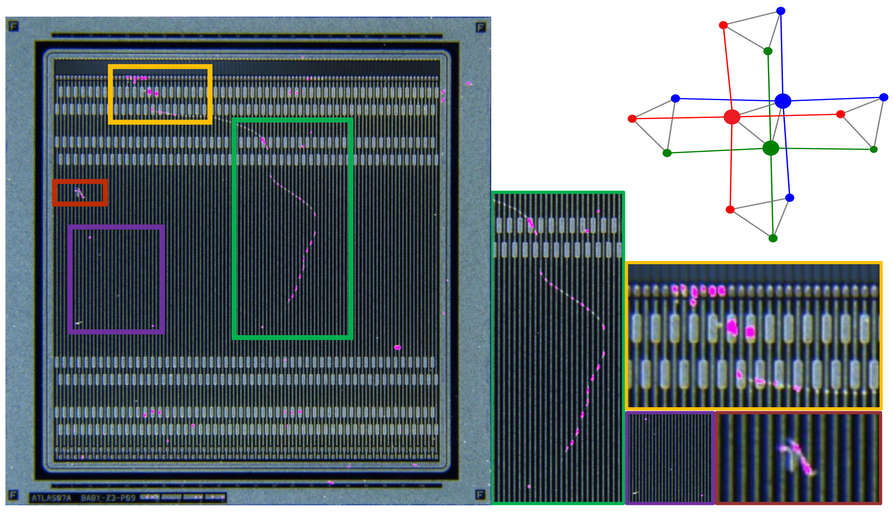


- Frequent false positives
- Misses obvious defects
- Fails to identify large-scale structures

Method 2: Laplacian Anomaly Detection (LAD)

[Verdoja, Grangetto, 2018], arXiv:1802.09843v4 [eess.IV]

- To generalize, the inverse covariance is replaced with the Laplacian, L, which accounts for both spectral and spatial weights
- The graph is expanded to connect the nearest neighboring pixels
- The new distance metric is $\delta(\mathbf{x}) = (\mathbf{x} - \hat{\mu})^T L (\mathbf{x} - \hat{\mu})$

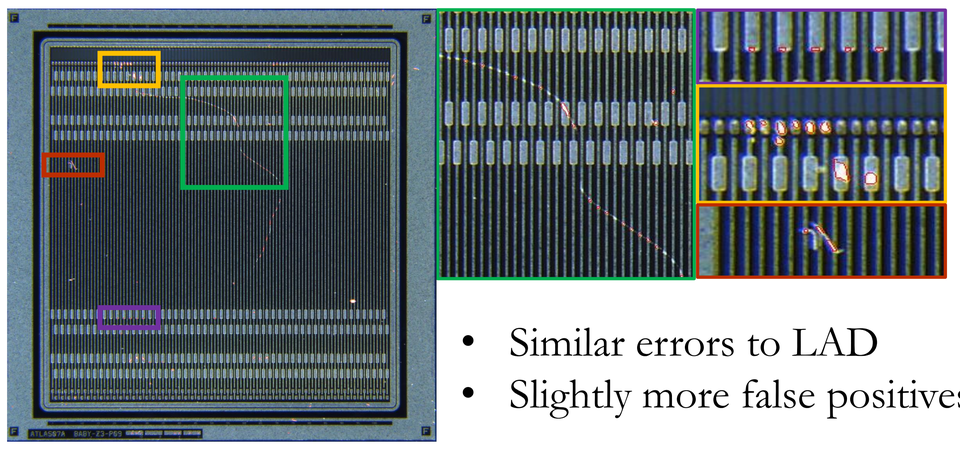


- Flags almost all defects
- Some false positives from reflections and dust
- Doesn't recognize continuity of large-scale structures

Segmentation

Method 1: Color-Distance Image Segmentation with Pruning

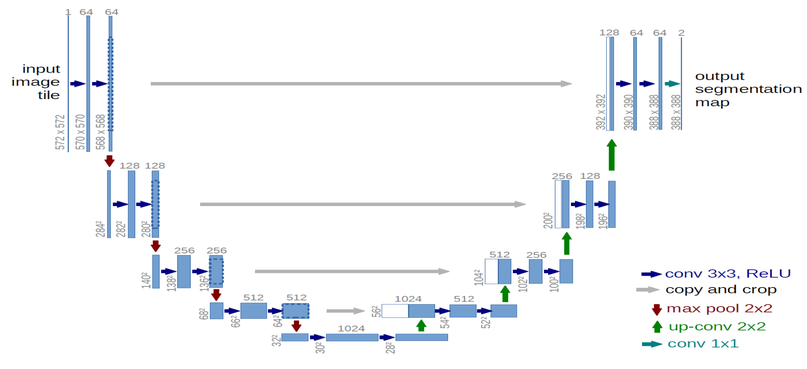
- Each pixel begins as a segment
- Loop over segments merging those with mean RGB vectors within some Euclidean distance, repeat until no more merging can occur
- Segments below a given size are merged with most similar segment
- Largest remaining segment is defined as background



- Similar errors to LAD
- Slightly more false positives

Method 2: Segmentation via Convolutional Neural Network (U-Net)

- Simple segmentation and outlier detection methods struggle with shapes and complex patterns
- Convolutional Neural Networks have shown success with such segmentation problems in the past, and U-Net requires little data (<100 images)
- Adding many modified images and linking convolutional and up-convolutional layers allows retention of more high-res information



Moving Forward

- Visual inspection can be automated using defect detection algorithms, but simple methods struggle with false positive rates and complex patterns
- Outlier detection has few assumptions, but has inadequate performance and is hard to optimize
- U-Net should resolve these issues, but requires more time. More results to follow soon…