Automated Visual Inspection of ITk Sensors

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WNPPC

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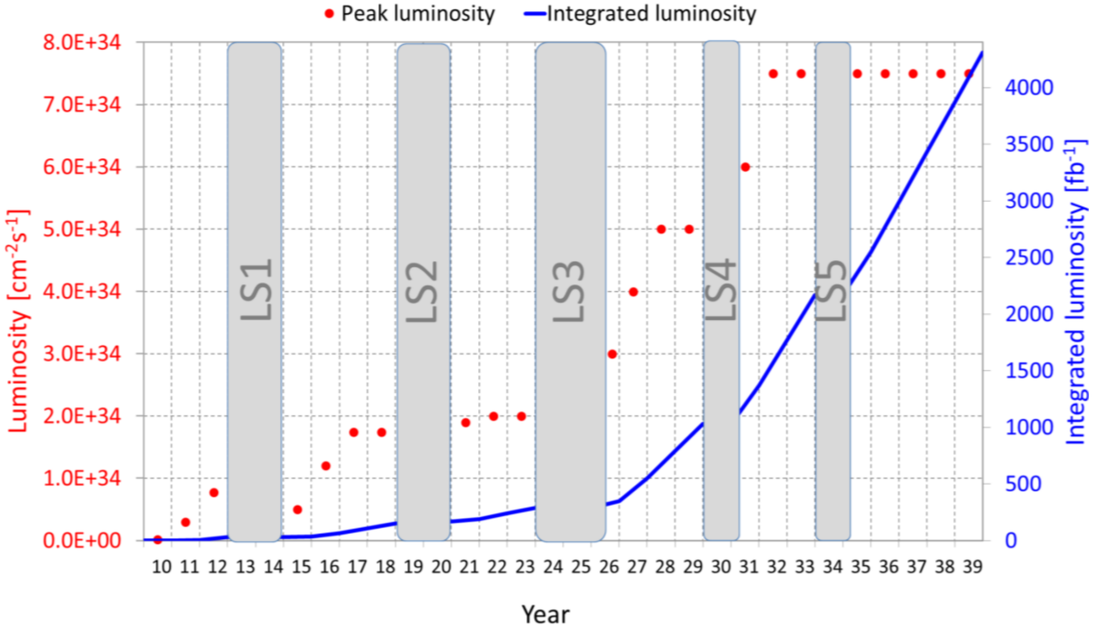
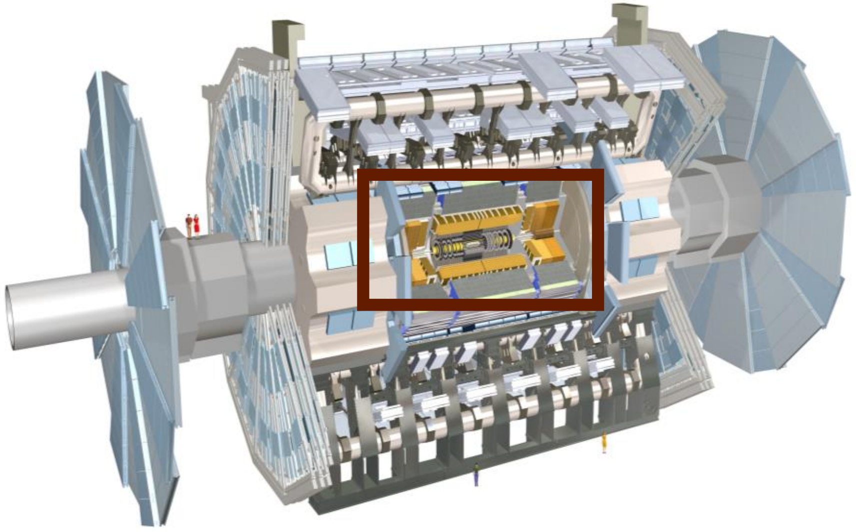
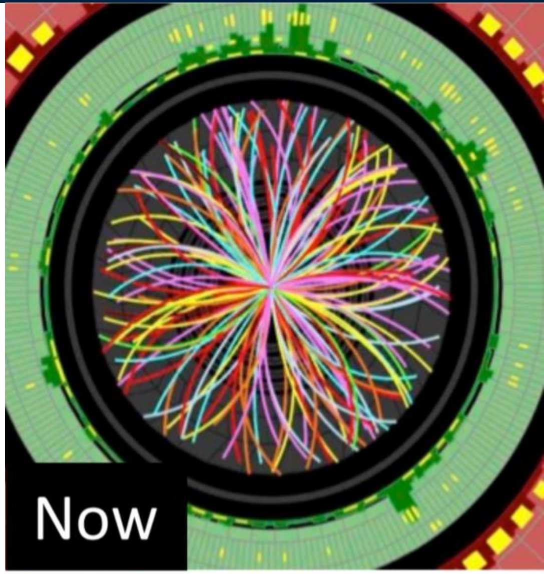
ATLAS and its new Inner Tracker (ITk)

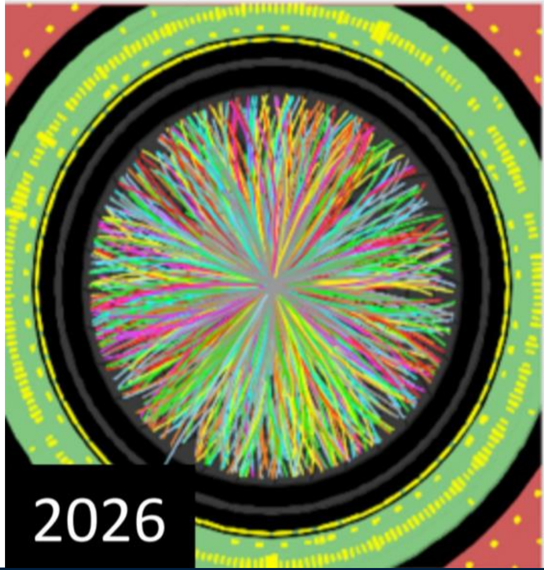
- Tracking gives particle momentum, charge, and info about decays
- Increase in luminosity requires improved central tracking system





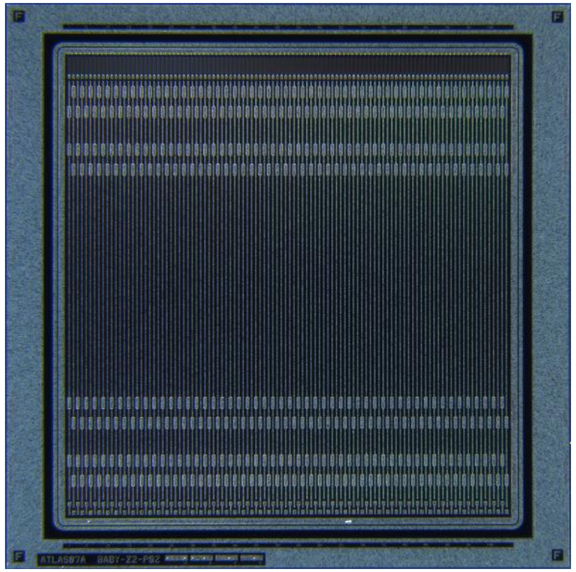
ATLAS Detector (CERN-GE-0803012-04, Joao Pequenao)

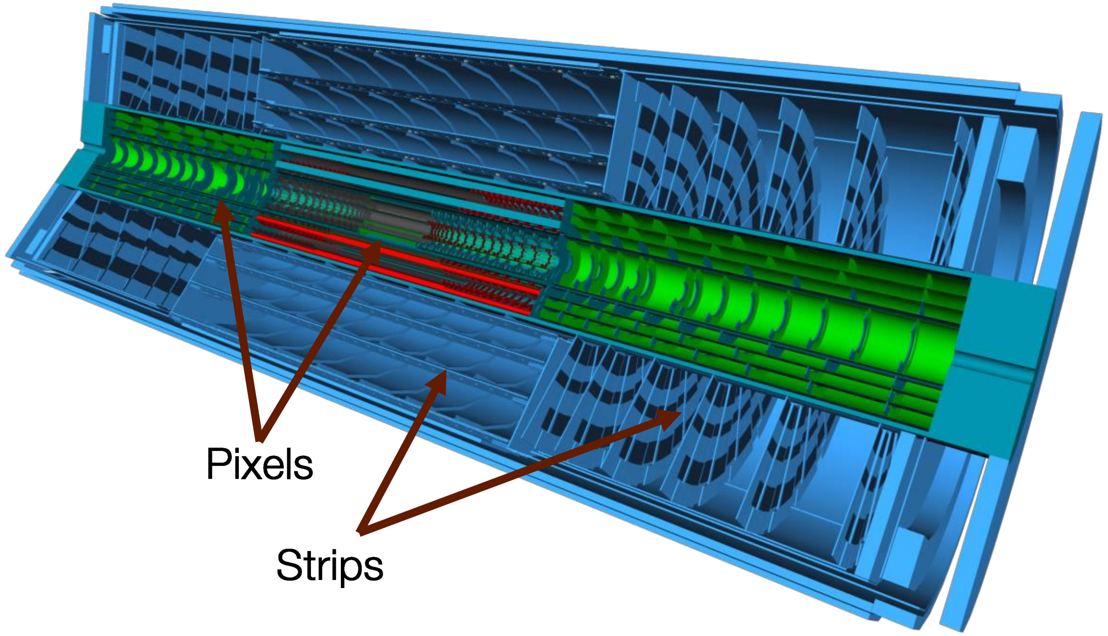




Inner Tracker (ITk)

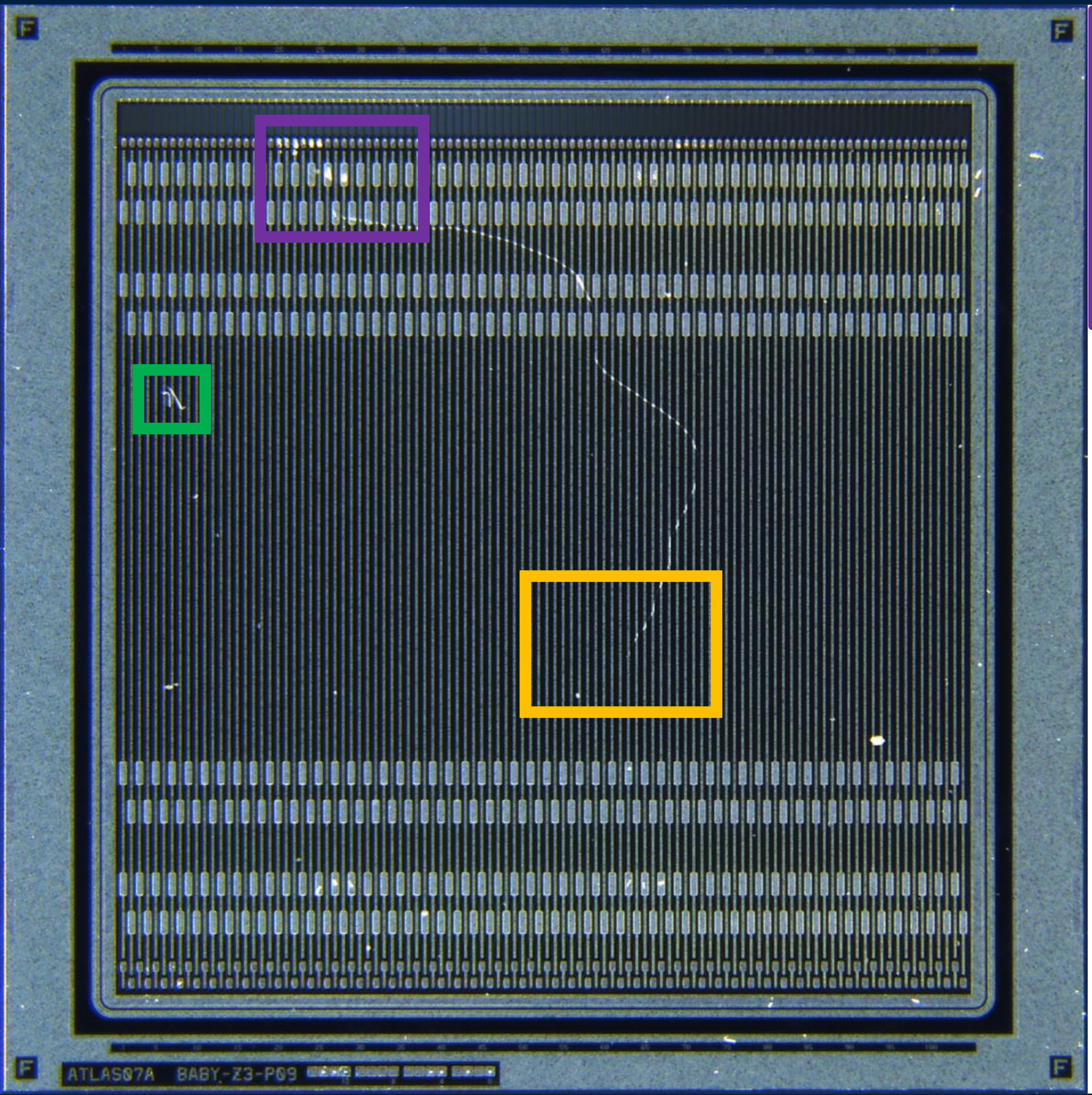
- The new Inner Tracker (ITk) replaces the old Inner Detector
- ITk is all silicon-hybrid detectors, but there are several geometries

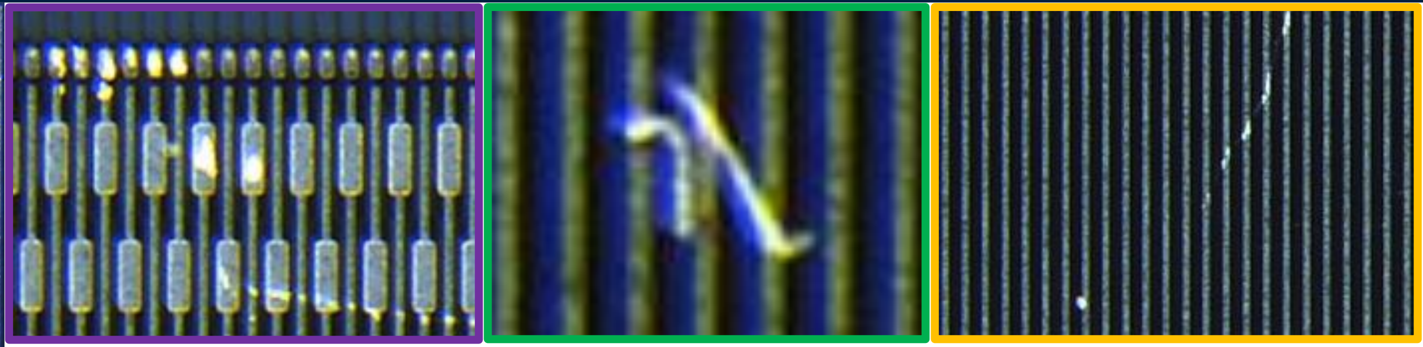




- All pictures used here will be of mini-prototypes of strip sensors

Visual Inspection & Goal of Automation





Task: Identify defects on the sensor

Current Method: Use a microscope and scan over the sensor by eye

Issues: Time consuming, tedious, likely inconsistent

Solution: Take pictures with an automated image stitching microscope and use machine learning/other algorithms to detect defects from that image

Methods of Automation

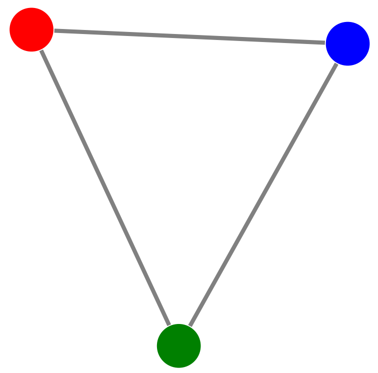
Goal: Flag defective regions

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

Defect Detection as Outlier Detection

Goal: Learn a probability distribution over pixels for all pixels



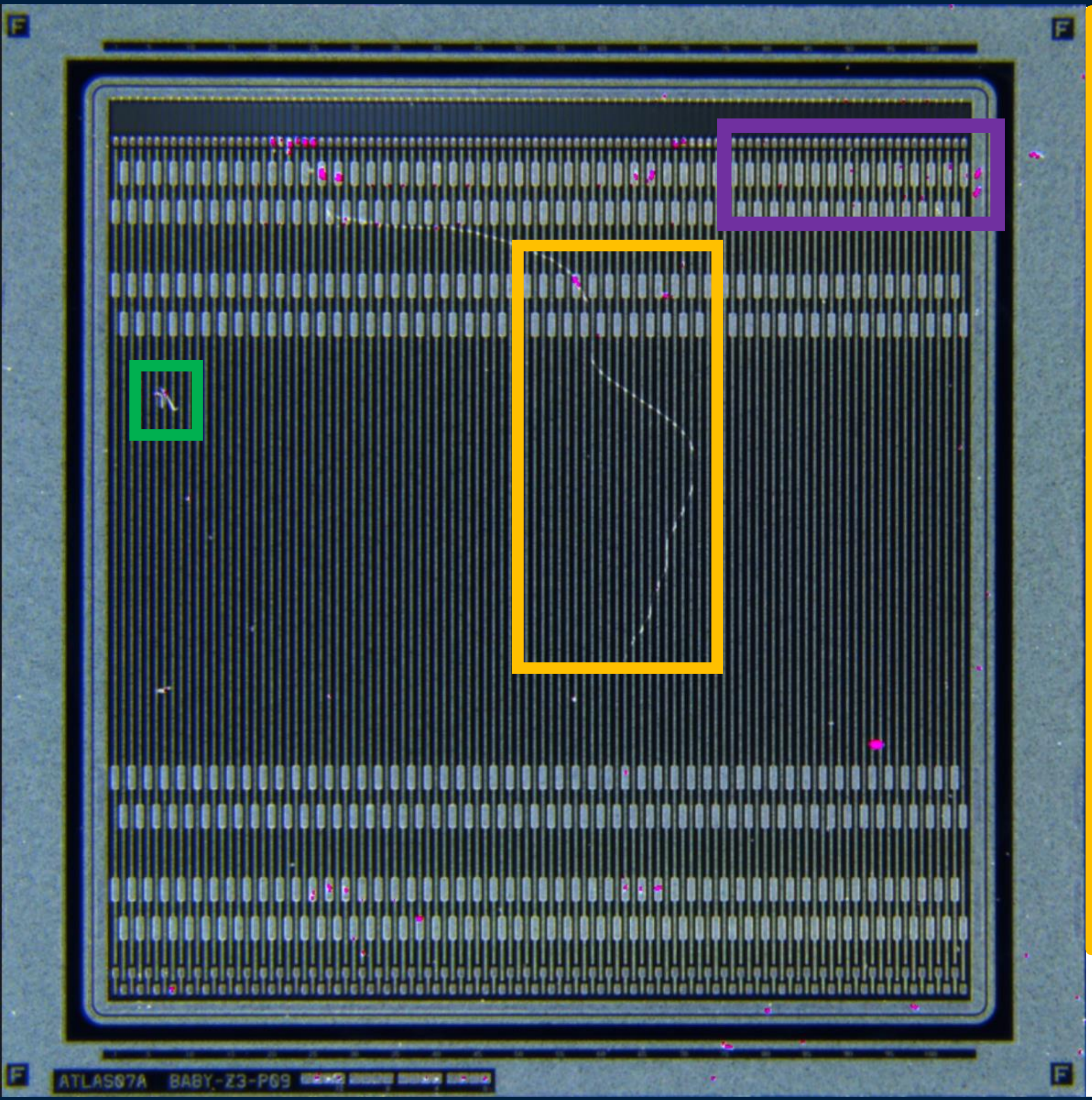
Solution 1: Reed-Xiaoli Detector (RXD)

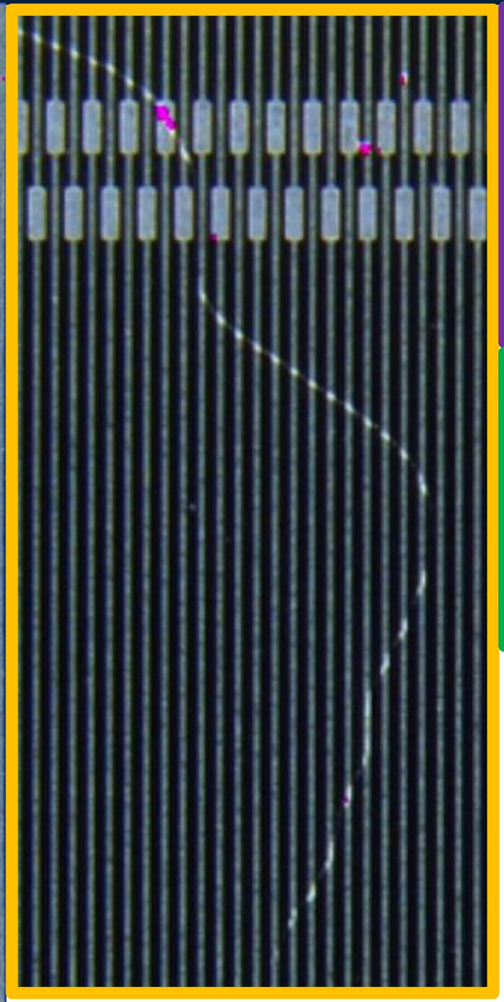
- Each pixel in the image $\mathbf{X}$ follows the same multivariate Gaussian
- Calculate sample mean $\hat{\mu}$ and covariance $\hat{C}$ of colours (RGB)

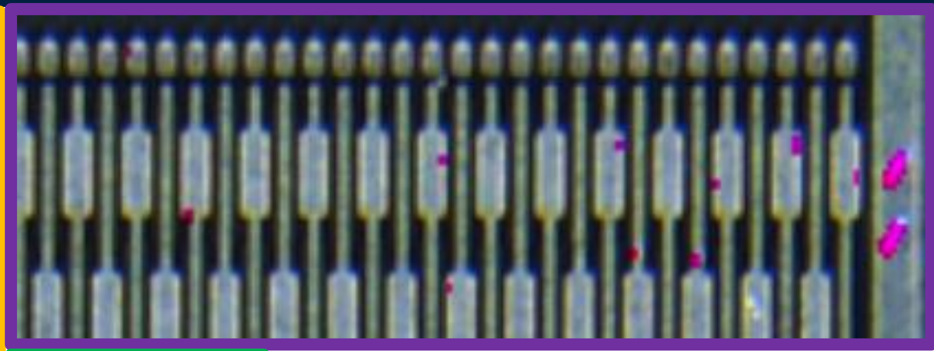
$$\delta(\mathbf{x}) = (\mathbf{x} - \hat{\mu})^T \hat{C}^{-1} (\mathbf{x} - \hat{\mu})$$

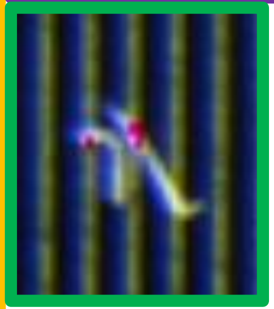
RXD – [Reed, Yu, 1990], DOI: 10.1109/29.60107

Reed-Xiaoli (RX) Detector





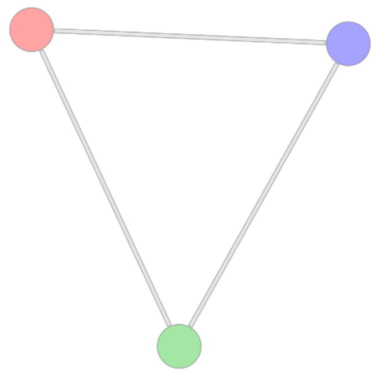




- Misses most of scratch
- Misses most of thread
- Frequent false positives

Defect Detection as Outlier Detection

Goal: Learn a probability distribution over pixels for all pixels



Solution 1: Reed-Xiaoli Detector (RXD)

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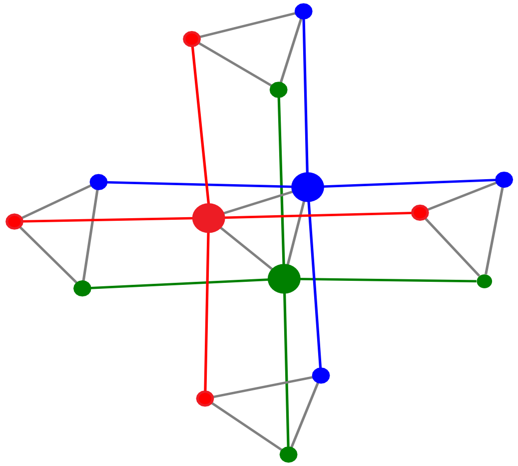
- Calculate sample mean $\hat{\mu}$ and covariance $\hat{C}$ of colours (RGB)

$$\delta(\mathbf{x}) = (\mathbf{x} - \hat{\mu})^T \hat{C}^{-1} (\mathbf{x} - \hat{\mu})$$

Solution 2: Laplacian Anomaly Detection (LAD)

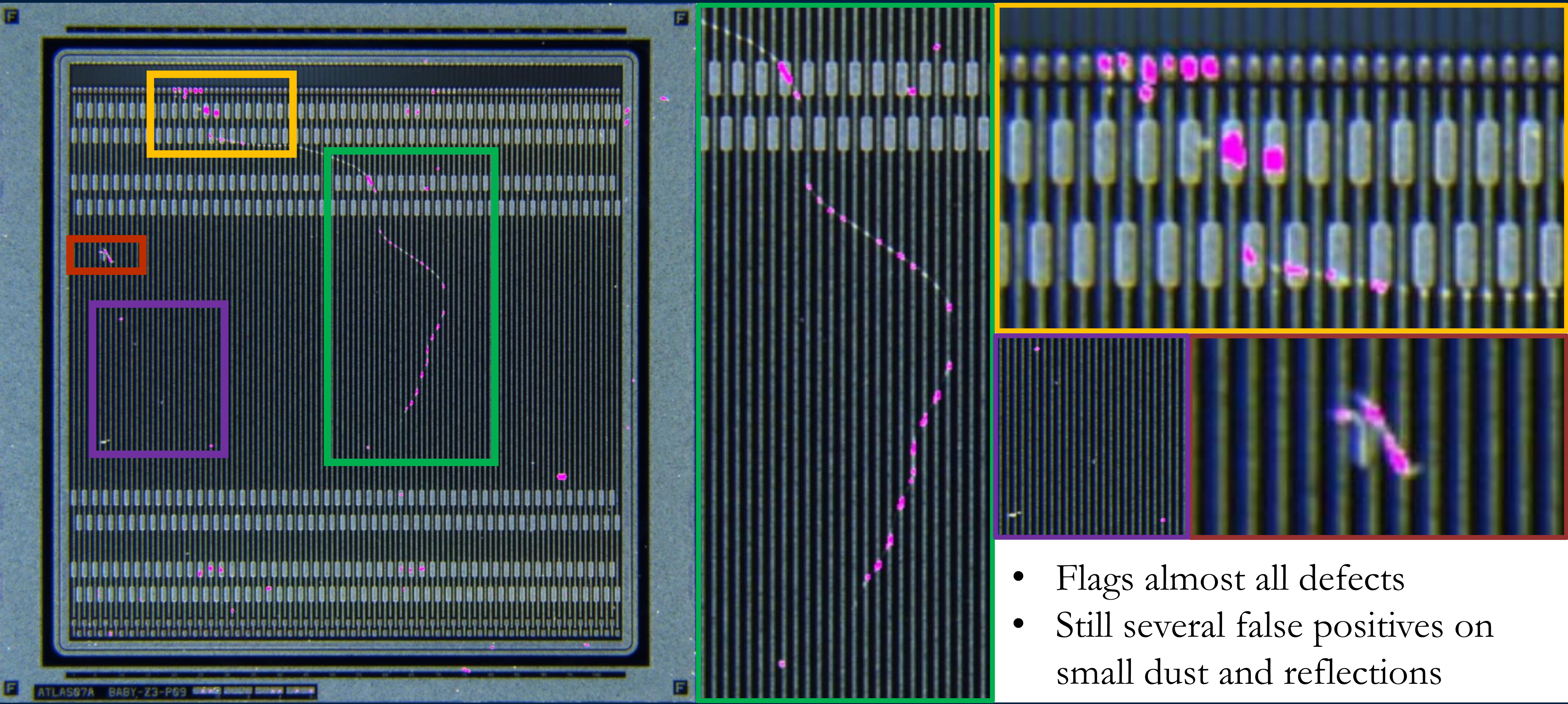
- Pixels are now also correlated with their neighbors
- L replaces $\hat{C}^{-1}$, it contains both spatial and spectral weights

$$\delta(\mathbf{x}) = (\mathbf{x} - \hat{\mu})^T L (\mathbf{x} - \hat{\mu})$$



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

Laplacian Anomaly Detection



- Flags almost all defects
- Still several false positives on small dust and reflections

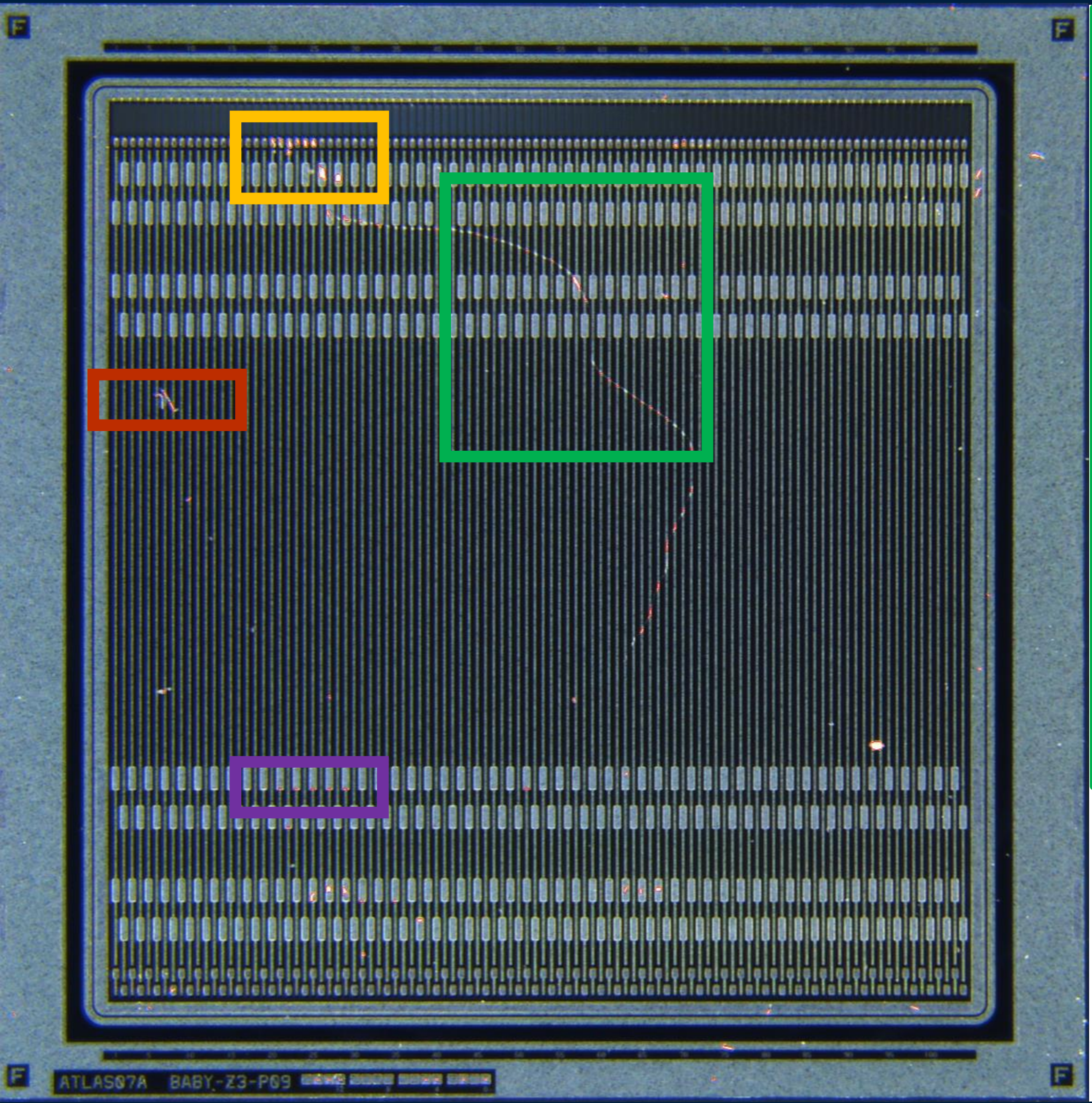
Defect Detection as Image Segmentation

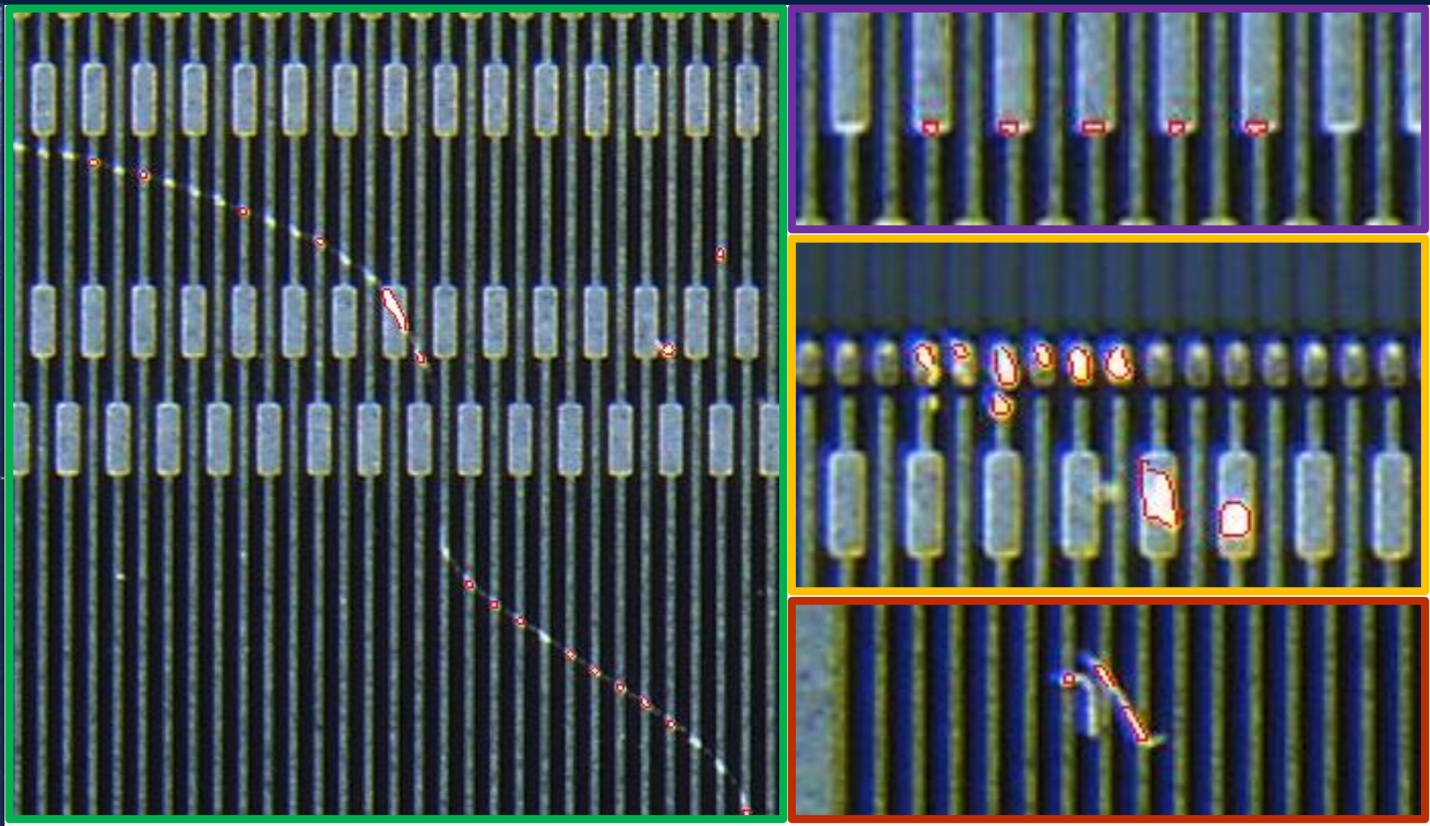
Goal: Learn criteria for segment splitting and background segment selection

Solution 1: Colour-Distance Segmentation with segment pruning

- Each pixel begins as a segment
- Calculate Euclidean distance between mean RGB vectors of any two segments
- If the distance does not exceed the given threshold, merge the segments
- Segments under size threshold are merged with the most similar segment
- The largest segment or that closest to the mean image colour, is the background

Colour-Distance Segmentation





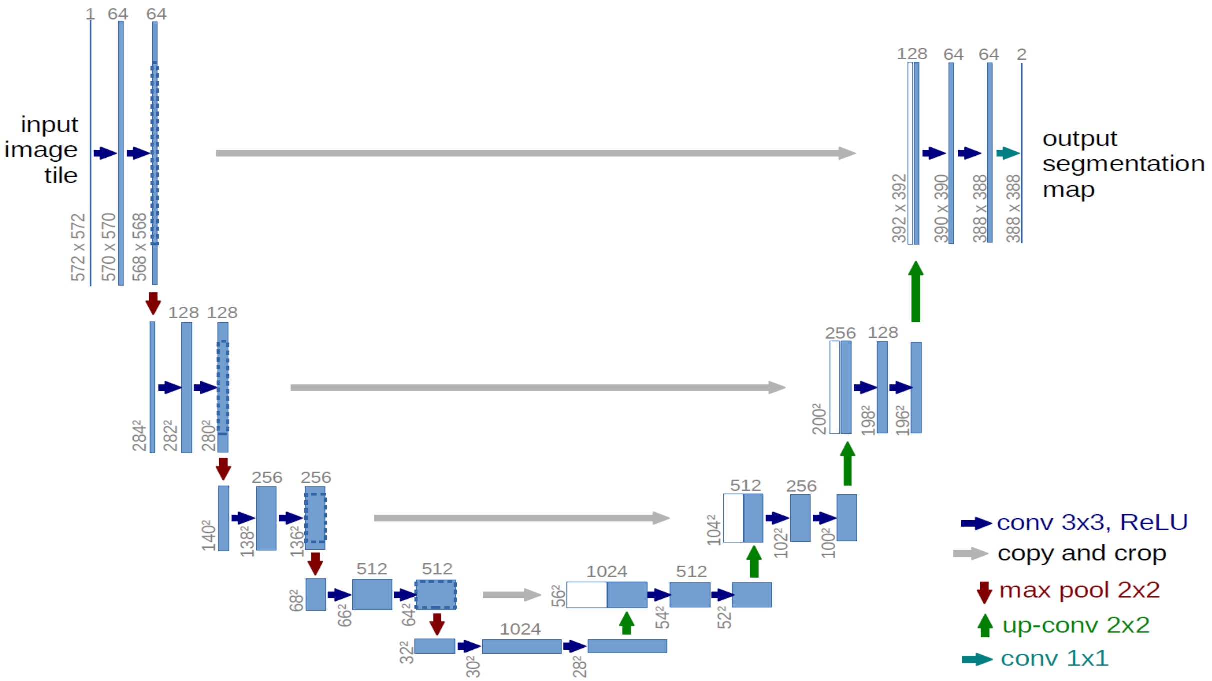
- Performs quite well, but still makes continuity errors and has slightly more false positives than LAD

Moving Forward: U-Net

Problem: Simple segmentation algorithms can’t learn complex enough patterns

Solution: U-Net

- Regular neural networks require large amounts of data



- U-Net’s architecture allows it to maintain pixel-level features despite compressing the information with each layer

- Adding many transformed (reflected, rotated) images and z-standardizing images allows U-Net to learn from even <100 images

Summary

- Increases in luminosity require improved tracking and thus, the new Inner Tracker (ITk)
- ITk sensors require visual inspection. Doing this manually is slow, tedious, and inconsistent
- This visual inspection can be automated using defect detection algorithms
- Outlier detection methods make fewer assumptions and improve significantly with growing complexity. However, while LAD shows the best performance of all the models it still has frequent false positives and much more data is required to extend outlier detection further
- Colour-Based Segmentation works well; however, false positive rates are too high and some complex defects are not fully identified despite heavy optimization
- More advanced segmentation algorithms like U-Net should resolve these issues while keeping data requirements sufficiently low