Optical quality assurance procedures for the sensors of CBM STS Detector

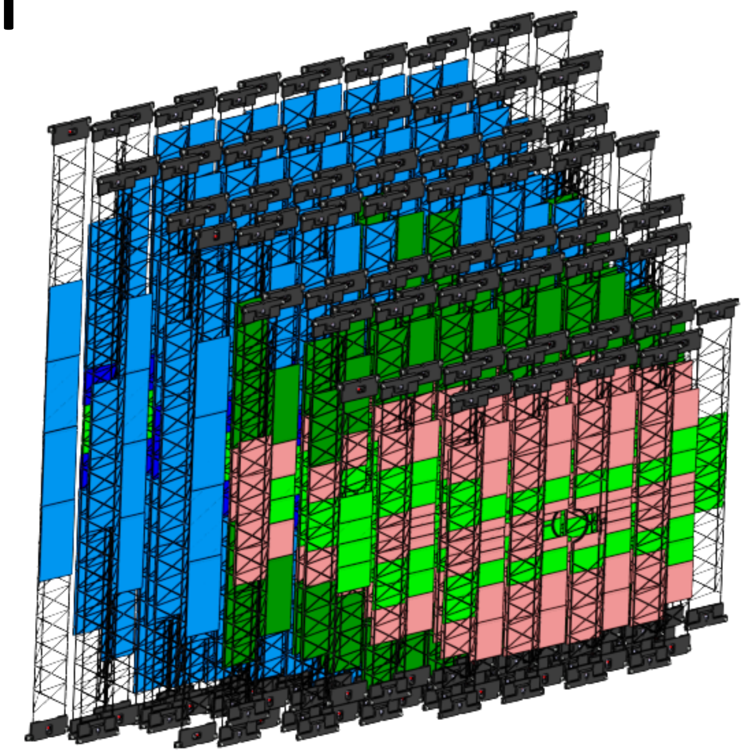
Evgeny Lavrik,
Eberhard-Karls Universität Tübingen
for CBM Collaboration

Overview

- Optical inspection setup
  - Overview
  - STS Sensors
  - Inspection principles
  - Capabilities
  - QA software
- QA Database
- Machine learning approach for QA
- Summary

Silicon Tracking System (STS) detector

- Compact detector built out of ~900 silicon microstrip sensors
- 8 layers of sensors
- 4 sensor size types
- 2 sensor vendors

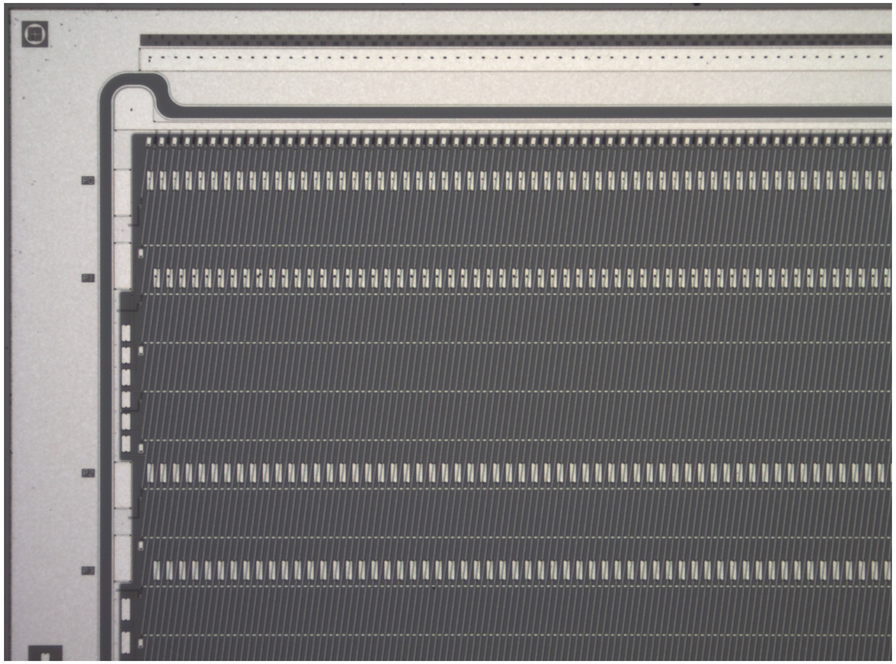


STS detector without thermal insulation

STS Sensors

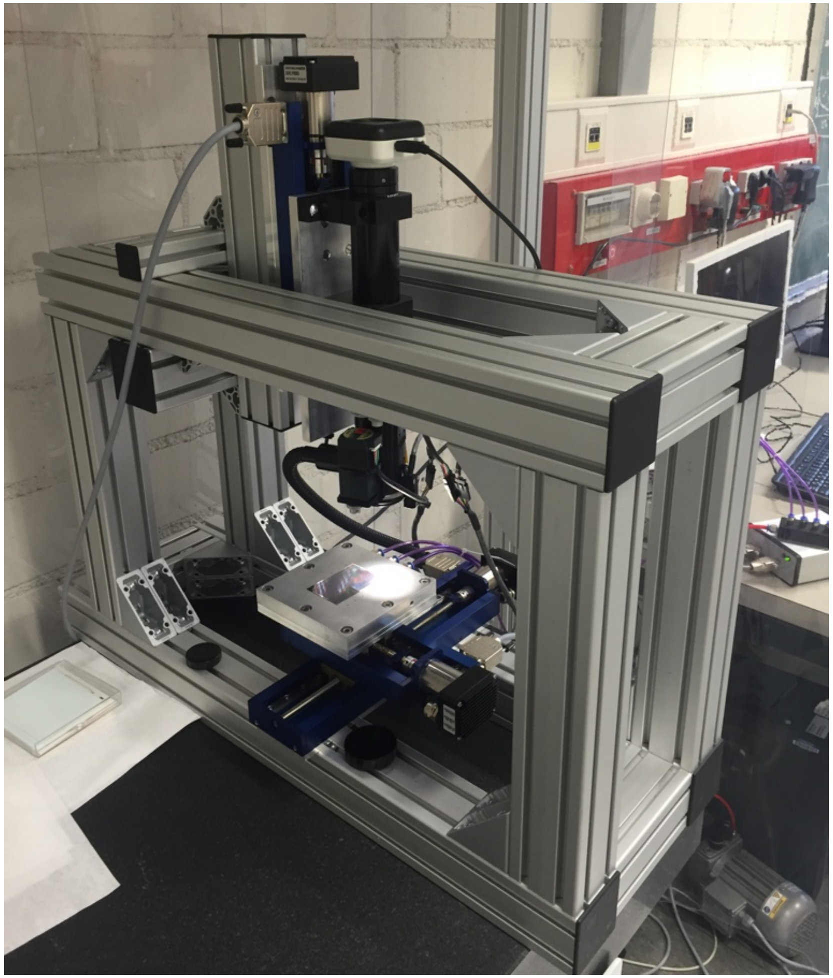
- Double-sided micro strip Si sensor
- 0° (n-side), 7.5° (p-side) stereo angle
- 58 µm strip pitch
- 1024 strips per side
- 6.2x12.2, 6.2x6.2, 6.2x4.2, 6.2x2.2

cm^2 form factors
- 2 manufacturers (CIS, Hamamatsu)



Optical inspection setup

- Flexible design to support inspection of different objects (different sensor size-types from CIS and Hamamatsu, sensor micro-cable inspection), other metrology and microscopy tasks
- Low hardware dependence, adaptable to almost any hardware
- Configurable QA procedures as plug-ins
- Report building, storage, viewing and editing
- Constant improvement in performance (inspection times 1 hour -> 30 min per sensor side, faster with faster camera) and inspection quality

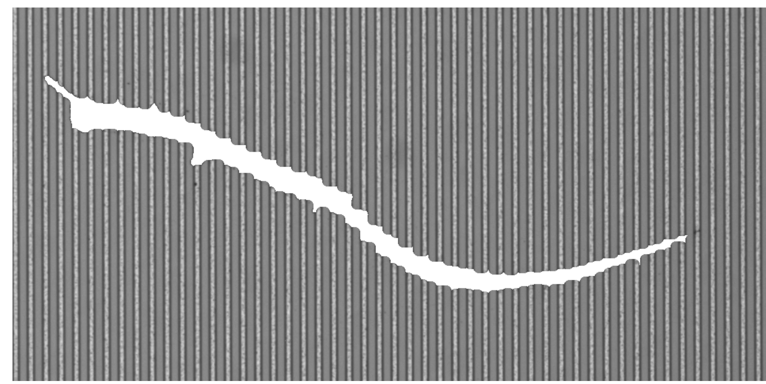


Inspection setup capabilities

Possible to detect:

- Dust particles and other foreign objects on the surface
- Scratches
- Single element integrity
  - bias resistors
  - strips
  - pads
  - guard ring
- Sensor edge defects & parallelity
- Possible any deviation from
  clean pattern (pattern/texture matching)
- Sensor warp inspection

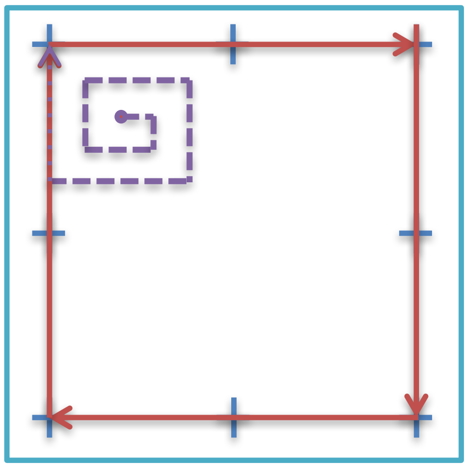
Edge profile



Recognized surface scratch

Setup evolved to the metrology station

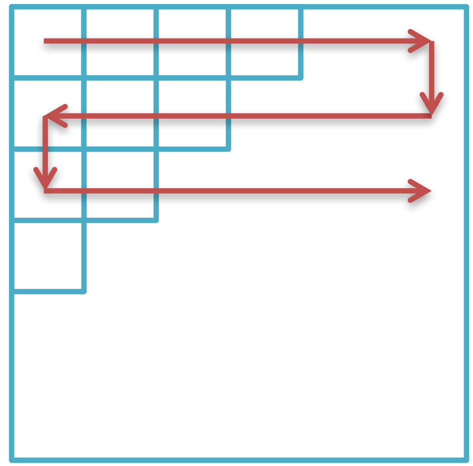
XY- and Z-stage calibration



Calibration movement pattern

$$\vec{x}_m = (S + C \cdot R) \cdot \vec{x}_s$$

Extract **S**tretching, **C**onversion, **R**otation matrices



Scan movement pattern

Images taken and sent to defect analysis

XYZ Stages has been characterized with a calibration plates

XYZ Positioning error ± 2.5 µm

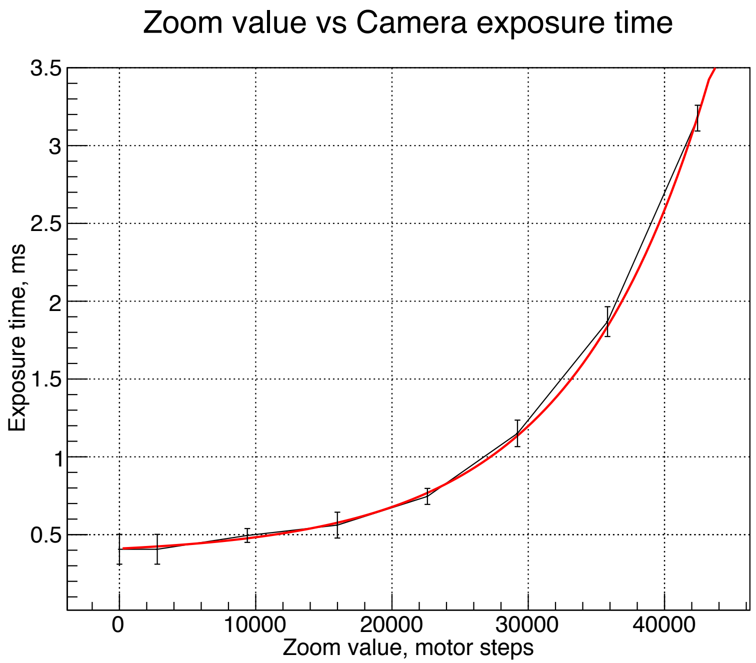
XYZ Repeatability error ± 1 µm

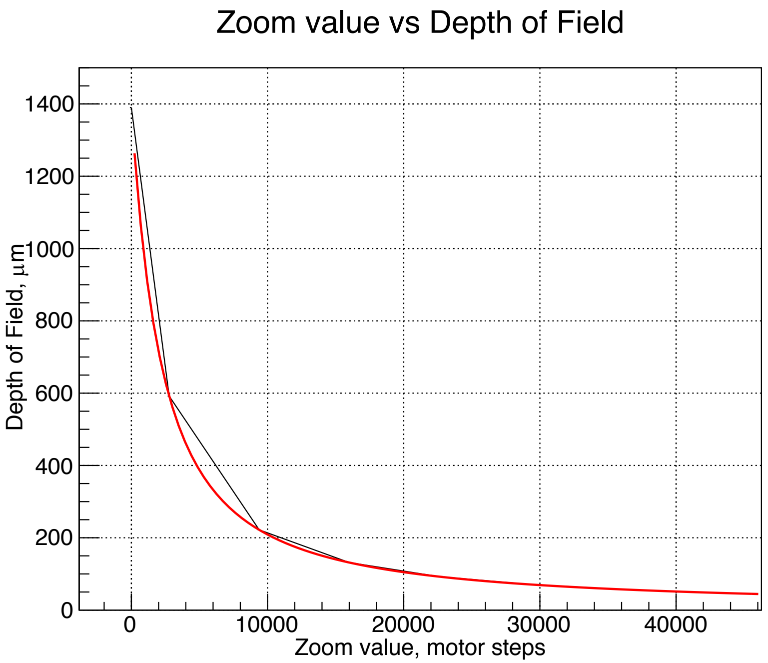
Y Stage faulty seeking

Current XY stage is a weak link
Too coarse for µm metrology-level applications

Optical axis calibration

Standard procedures to characterize optical system, HW independent



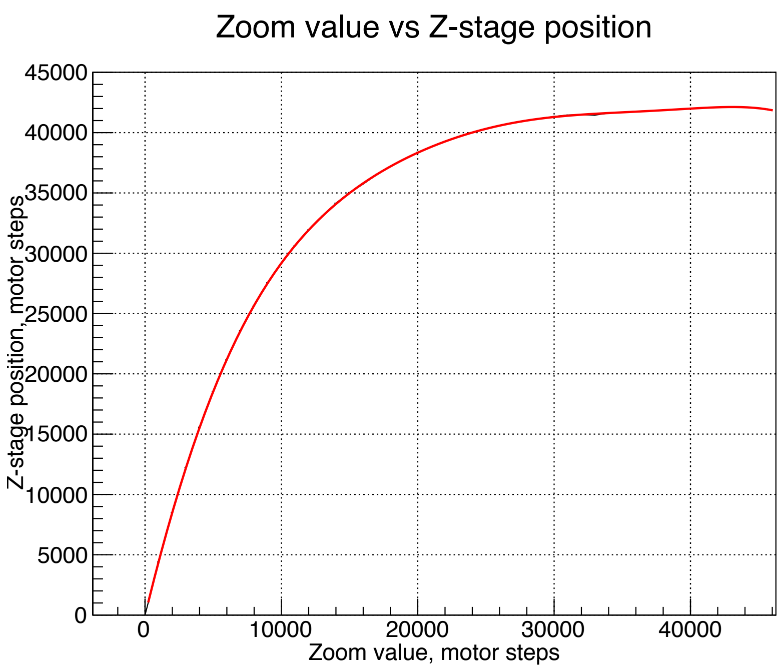


Camera properties.
Here exposure

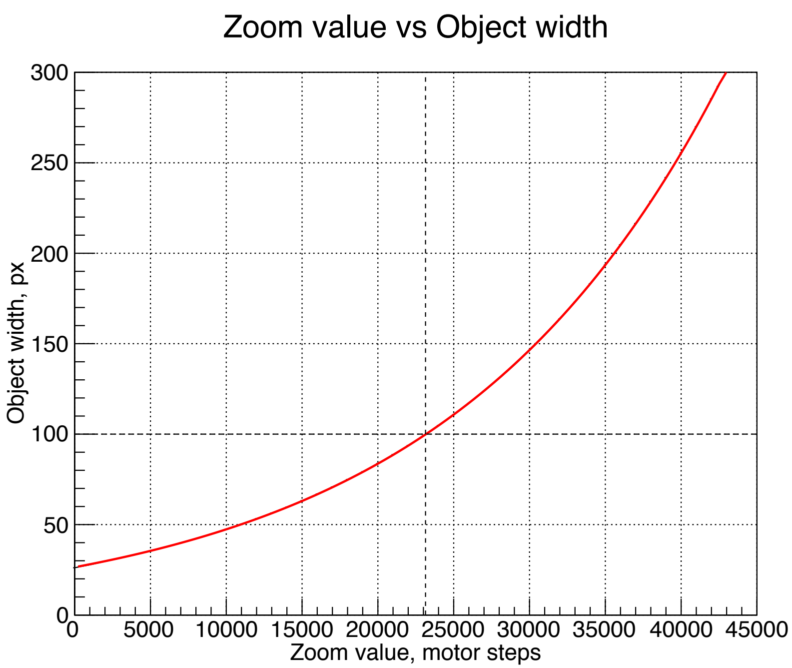
Height measurement parameters
Here depth of field, related to HWHM

Optical axis calibration

Standard procedures to characterize optical system, HW independent



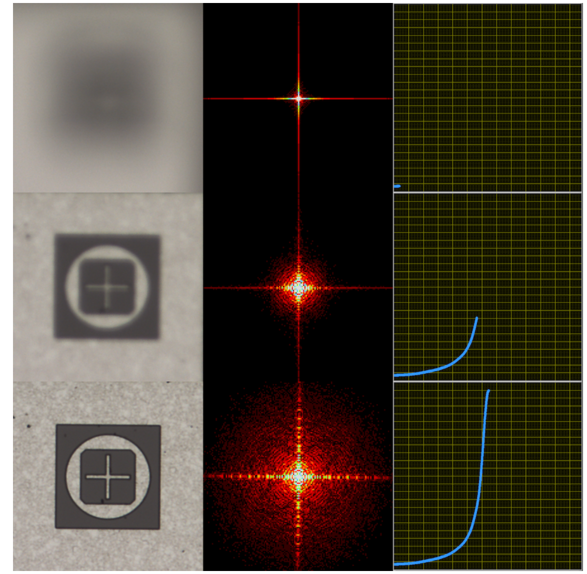
Software parfocality
Parcentricity to be addressed



Pixel to µm conversion ratio

Height measurements

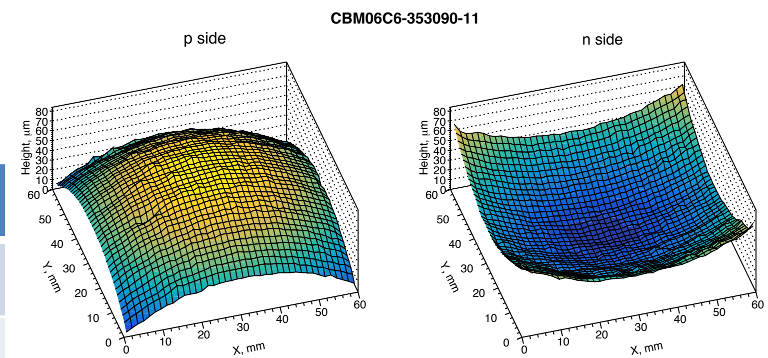
- Contactless, thus non-damaging method to measure heights
- Uses Focusing Stage of the inspection setup
- Differential measurements of most focused value, extracted from Lorentzian fit



- Measurements of Warp, Thickness

CIS		Hamamatsu	
„n-bulk“	strips	„n-bulk“	strips
303 µm	311 µm	331 µm	340 µm

Sensor thickness, measured on a single edge

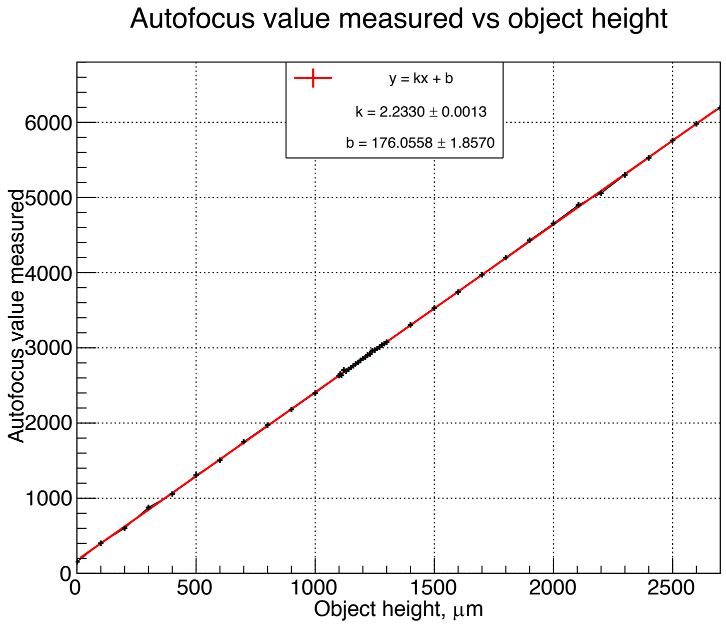


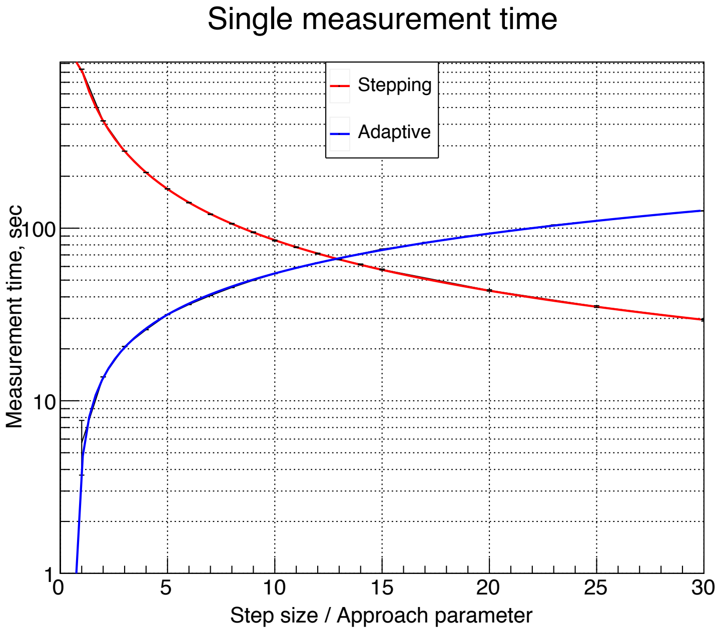
Height map (warp) of a CBM06C6 sensor

Sensor Warp Measurements

Calibration against a certified Mitutoyo gauge block set yields precision of ~1µm

Performance optimizations with adaptive method, speedup of 8-20 times

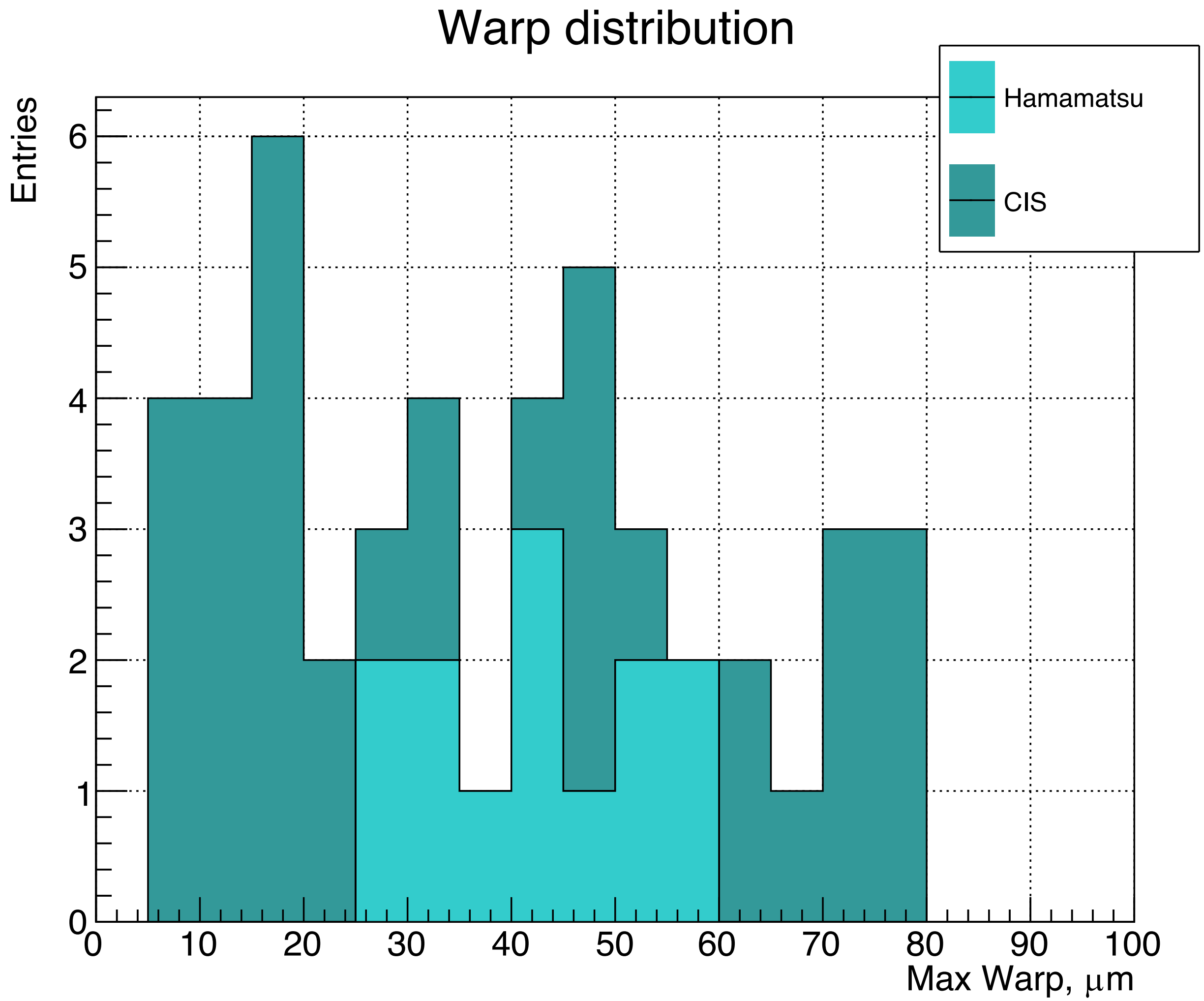




Meas step, mm	Adaptive method, hrs	Straightforward, hrs
1	13.75	106.12
2	3.43	26.53
3	1.5	11.8
4	52 min	6.63
5	33 min	4.2

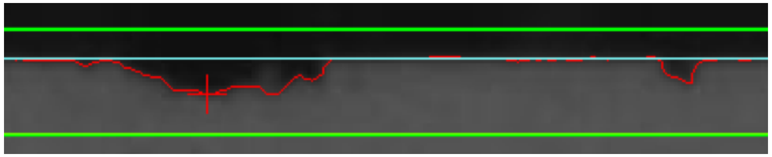
Warp measurement time of a 6x6 sensor

Sensor Warp for 20 sensors



Values of warp observed between 15 and 80 µm across prototype sensors, seemingly no dependence (yet?)

Sensor cutting edge



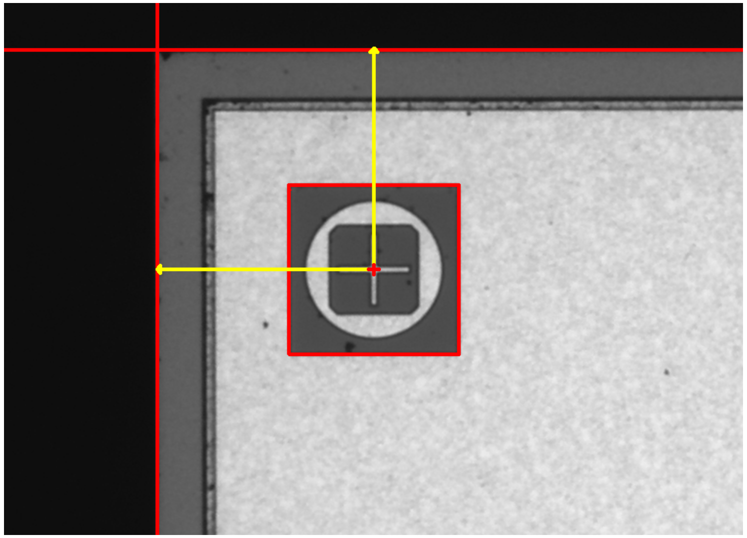
Cutting edge quality estimation

by looking at the deviation from fitted edge

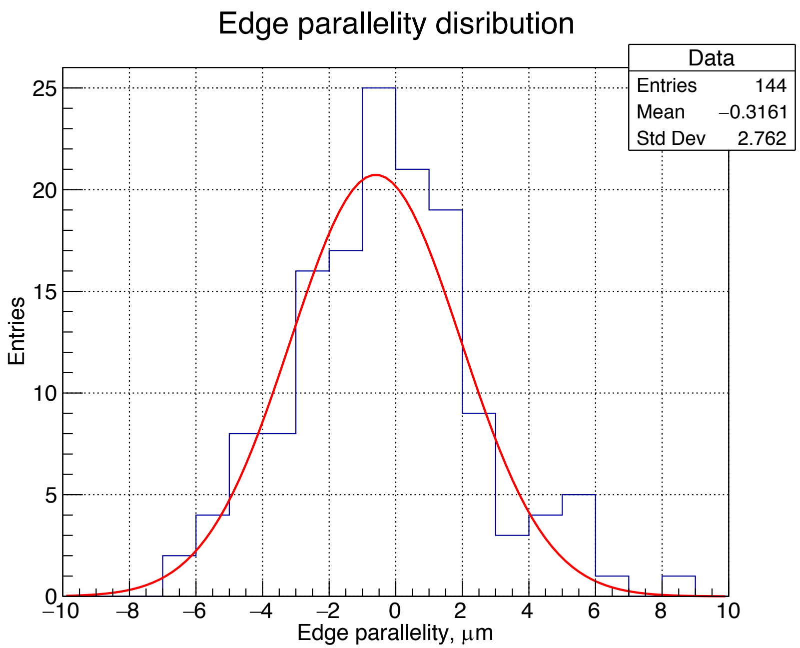
≤ 20µm

Cutting edge parallelity

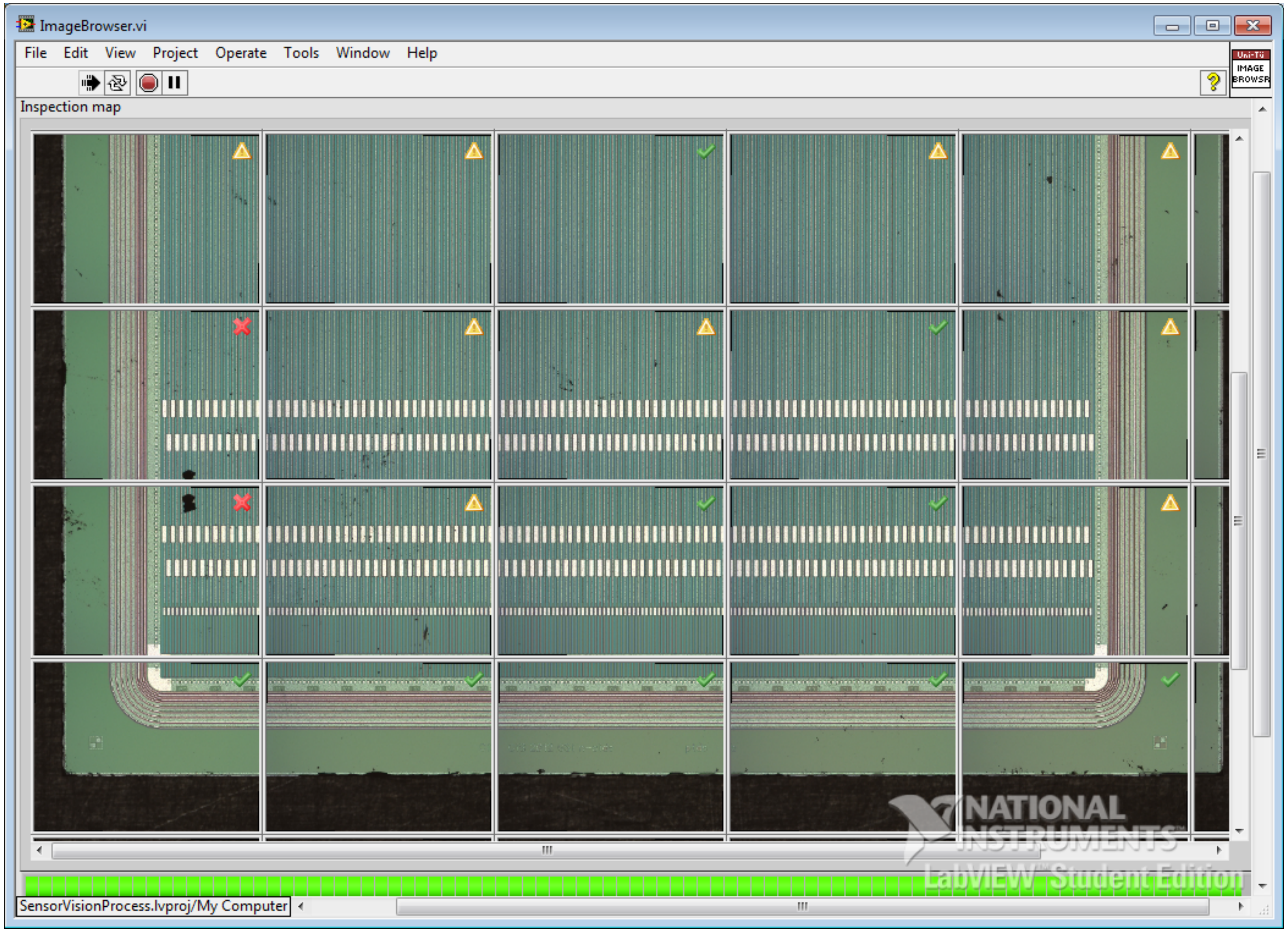
by looking at the distance from the alignment mark to the fitted edge at all 4 corners



Week. 20.03.2017

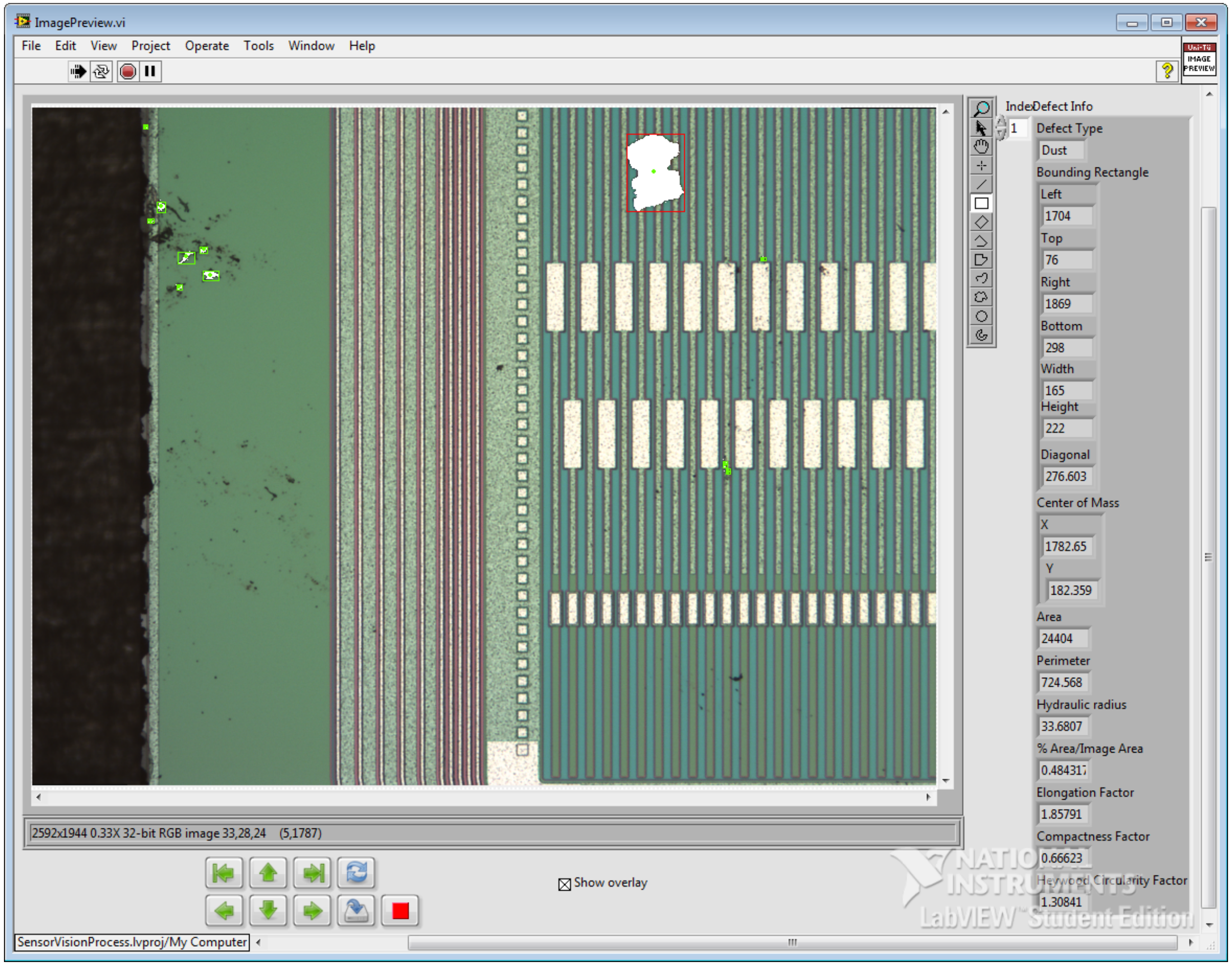


Inspection reports



Inspection results with detected defects, different annotation
Here a baby sensor for demonstration purposes

Inspection reports



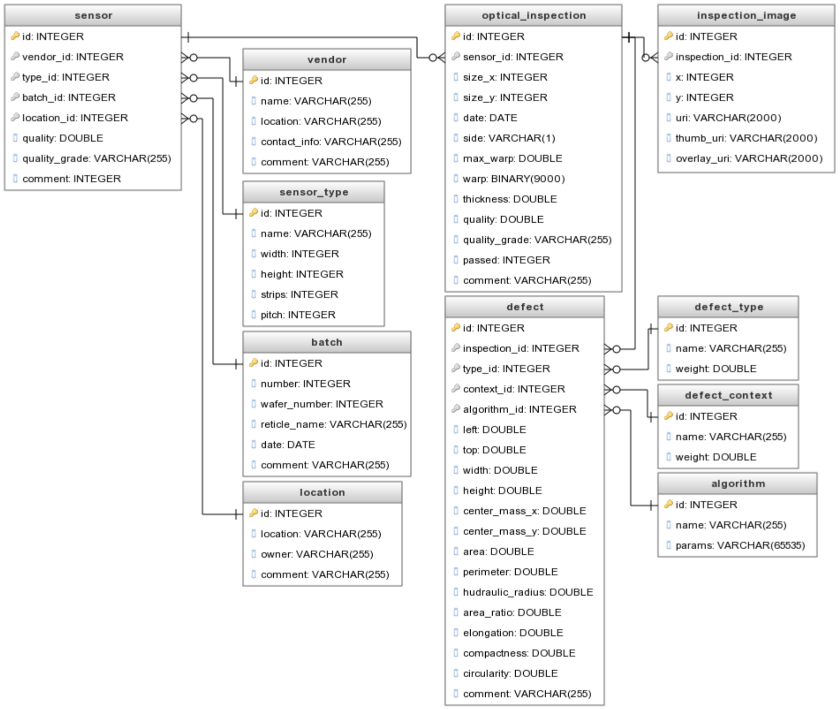
Single ROI with defects detected, defect information (class, center of mass, area, etc.)
Operators workplace with navigation, editing etc. functionality

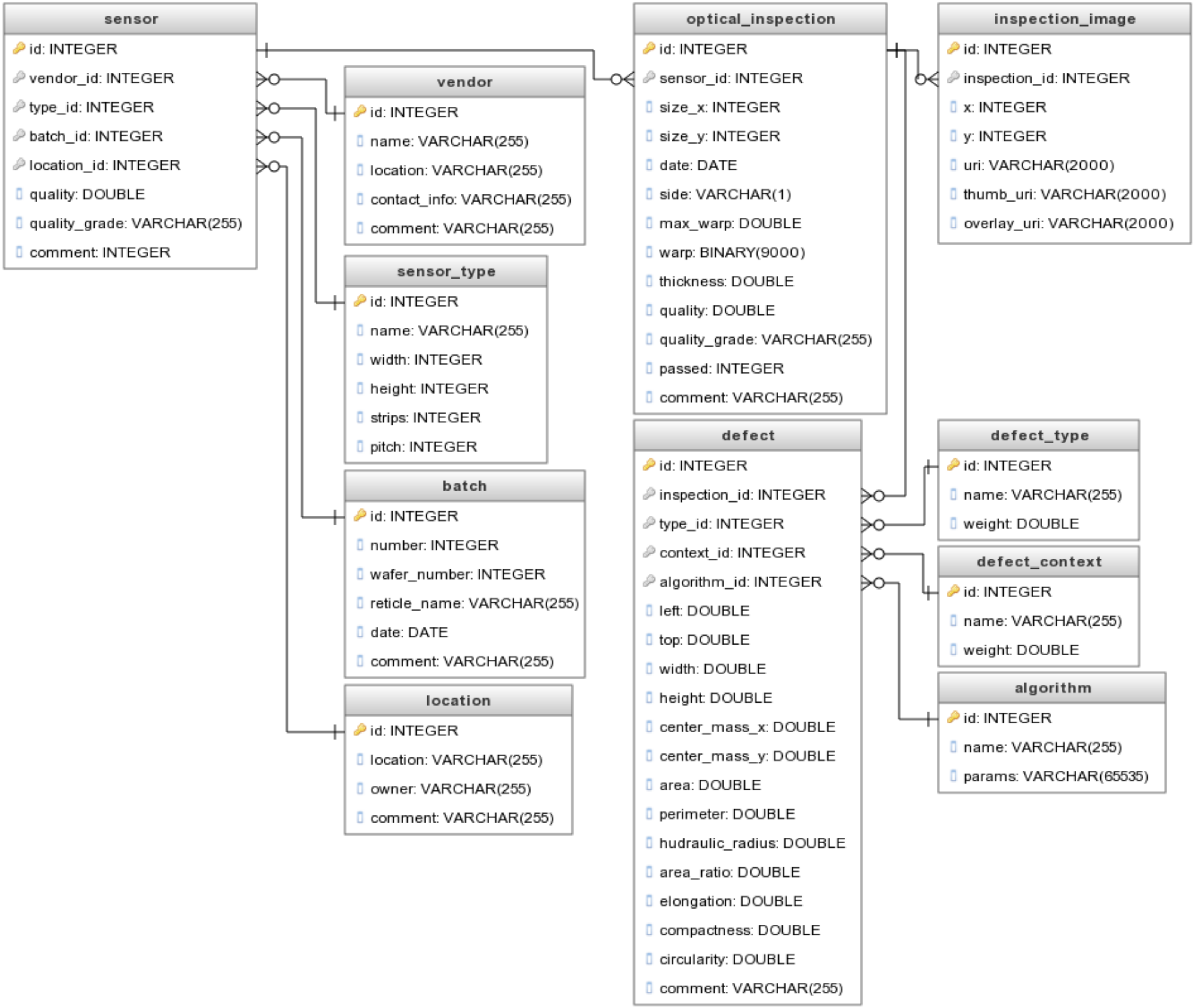
Database

- Reports formed during analysis to be stored in Database
- Centralised data storage for CBM – FairDB

- 1 full inspection is 12.2 GB per 6x6 sensor (n and p sides, lossless png)
- Up to 40 TB of images needs to be stored -> tape storage **gStore** from GSI

- Database interfaces are currently being developed




sensor
id: INTEGER
vendor_id: INTEGER
type_id: INTEGER
batch_id: INTEGER
location_id: INTEGER
quality: DOUBLE
quality_grade: VARCHAR(255)
comment: INTEGER
vendor
id: INTEGER
name: VARCHAR(255)
location: VARCHAR(255)
contact_info: VARCHAR(255)
comment: VARCHAR(255)
sensor_type
id: INTEGER
name: VARCHAR(255)
width: INTEGER
height: INTEGER
strips: INTEGER
pitch: INTEGER
batch
id: INTEGER
number: INTEGER
wafer_number: INTEGER
reticle_name: VARCHAR(255)
date: DATE
comment: VARCHAR(255)
location
id: INTEGER
location: VARCHAR(255)
owner: VARCHAR(255)
comment: VARCHAR(255)
optical_inspection
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sensor_id: INTEGER
size_x: INTEGER
size_y: INTEGER
date: DATE
side: VARCHAR(1)
max_warp: DOUBLE
warp: BINARY(9000)
thickness: DOUBLE
quality: DOUBLE
quality_grade: VARCHAR(255)
passed: INTEGER
comment: VARCHAR(255)
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inspection_id: INTEGER
type_id: INTEGER
context_id: INTEGER
algorithm_id: INTEGER
left: DOUBLE
top: DOUBLE
width: DOUBLE
height: DOUBLE
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center_mass_y: DOUBLE
area: DOUBLE
perimeter: DOUBLE
hudraulic_radius: DOUBLE
area_ratio: DOUBLE
elongation: DOUBLE
compactness: DOUBLE
circularity: DOUBLE
comment: VARCHAR(255)
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y: INTEGER
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overlay_uri: VARCHAR(2000)
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name: VARCHAR(255)
weight: DOUBLE
defect_context
id: INTEGER
name: VARCHAR(255)
weight: DOUBLE
algorithm
id: INTEGER
name: VARCHAR(255)
params: VARCHAR(65535)

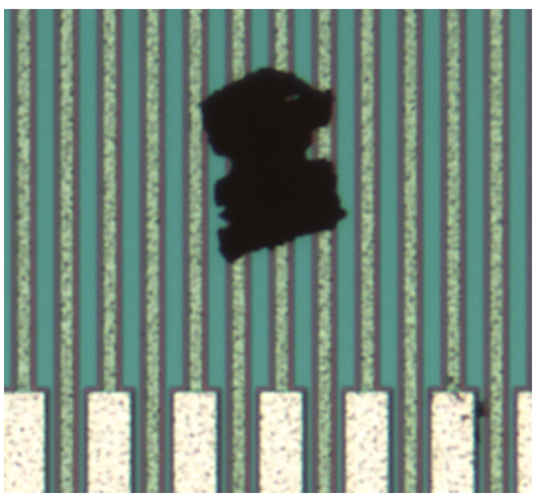
Detection in context

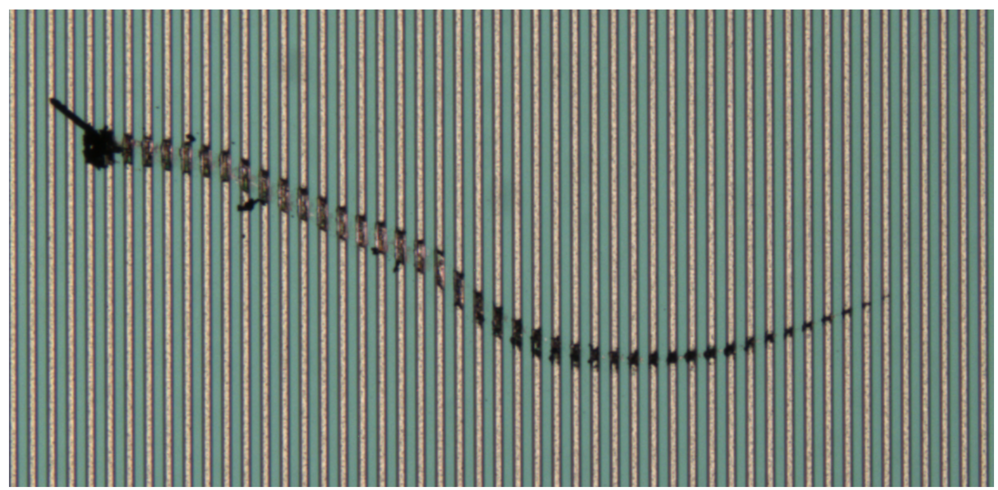
Problem: In direct light all surface defects appear as dark objects
How to differentiate between them?

Example: Dust particles cover strips and interstrip area,
Scratches appear mostly only on strips.

Knowing the context of defect affects its severity weighting

Currently identified by by pattern matching. Not universal.





Identifying the context

- Pattern matching does its job well, but needs to be supervised
- Adjusting the tresholds and matching scores during production phase is a bad design
- Idea: augment it with machine learning methods
- E.q. a classification neural network, which adapts itself to everchanging global data.

- The machine vision and machine learning enjoys a lot of academic interest in the last time with new ideas, models and software frameworks being constantly published

- A „Darknet“ framework with a model „You only look once“ has been taken into consideration for its performance and relative ease of use

arXiv:1612.08242v1 25 Dec 2016

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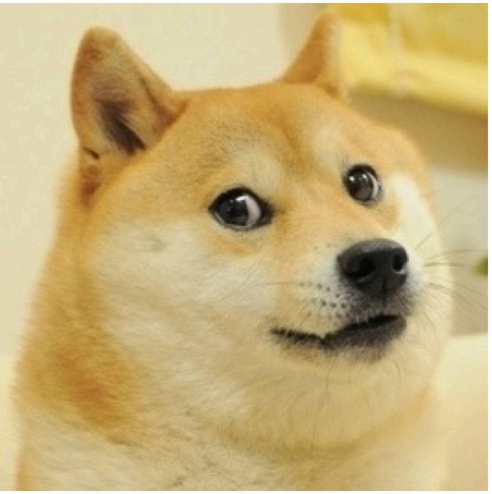

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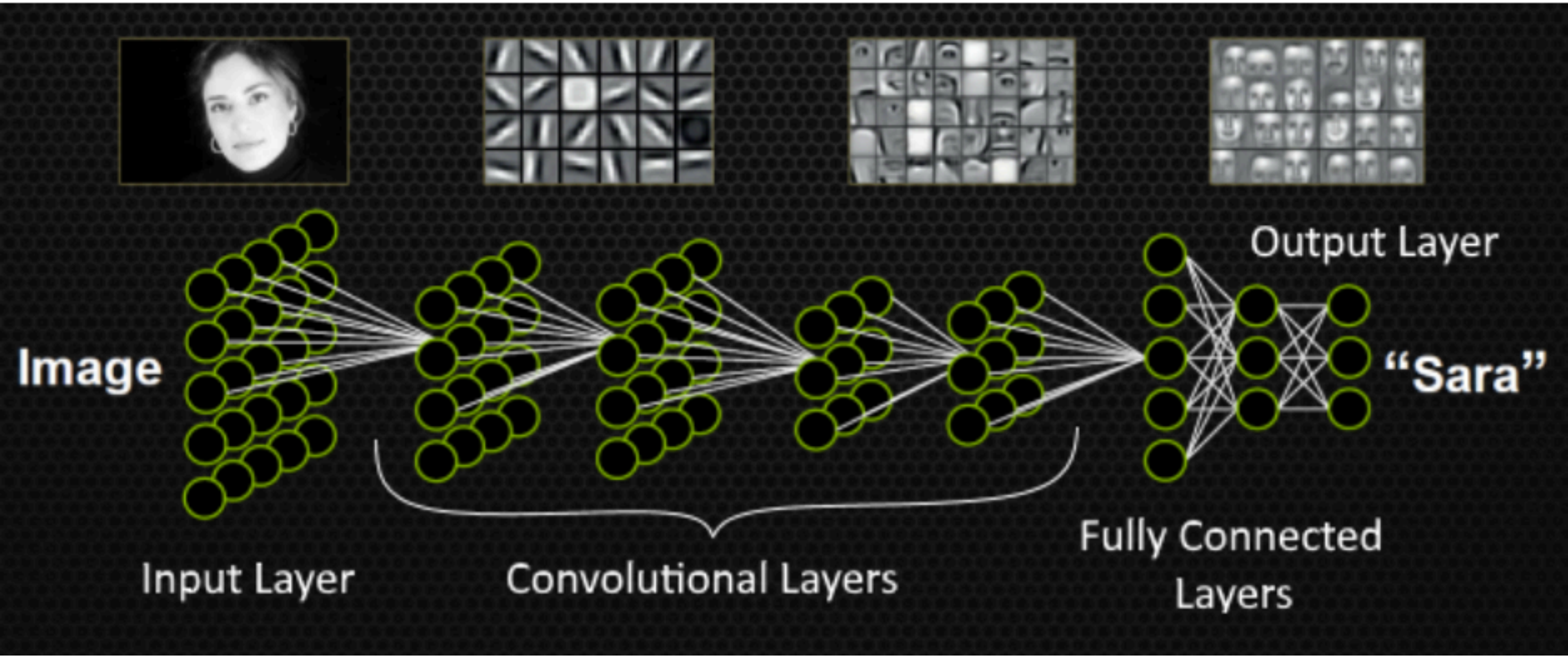
Neural networks

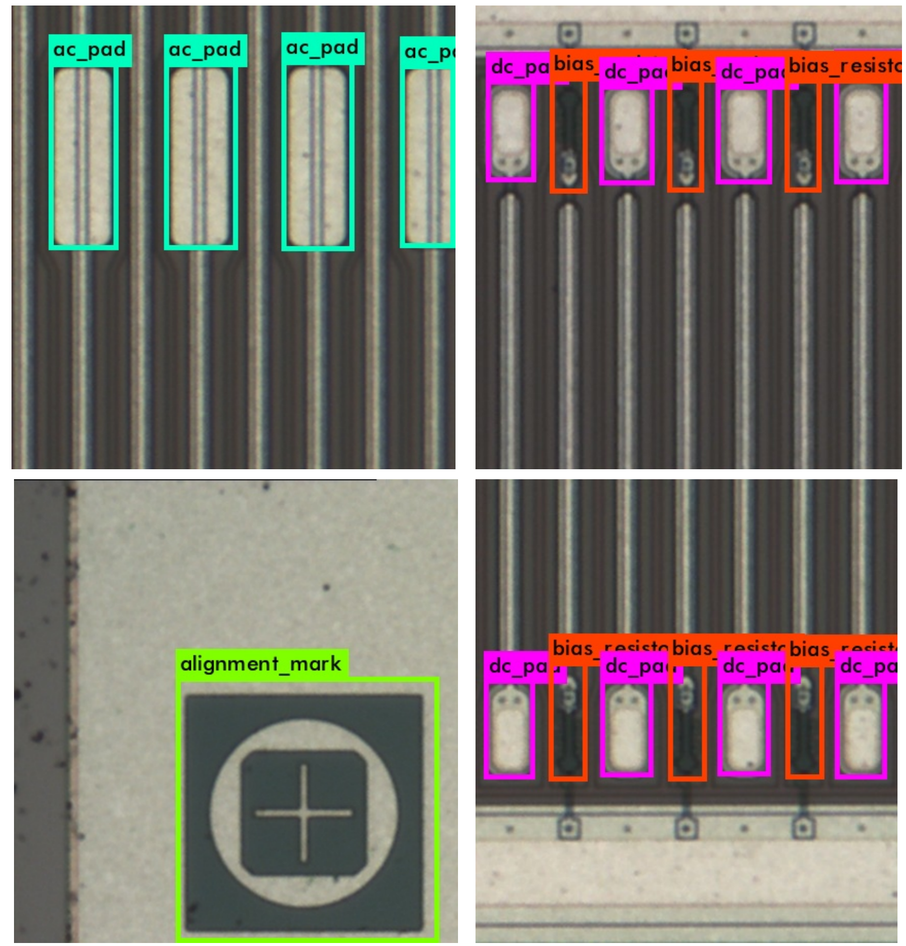
- YOLO is a fully convolutional deep neural network with a region proposal basis, but what does this mean?



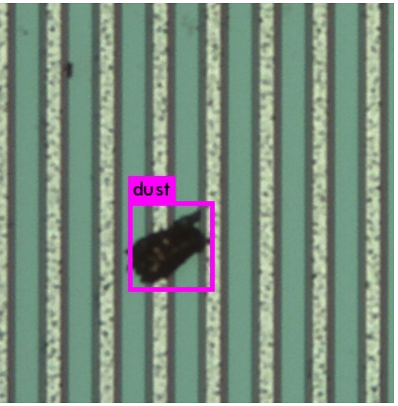
Applying it to our task

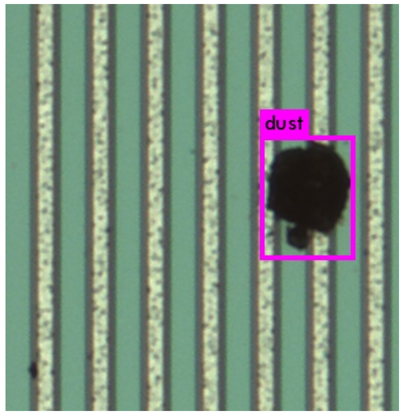
- Train on an imageset with features marked
- ~ 12 Hours on OEM GTX 745

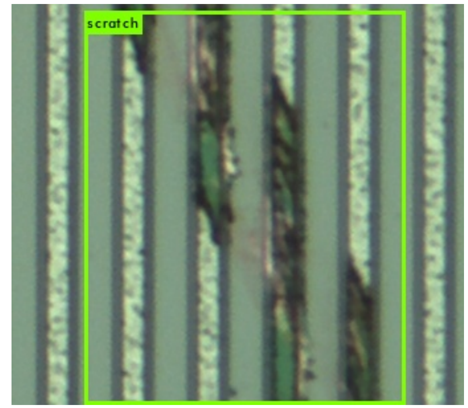
- Synthetic test shows a good output

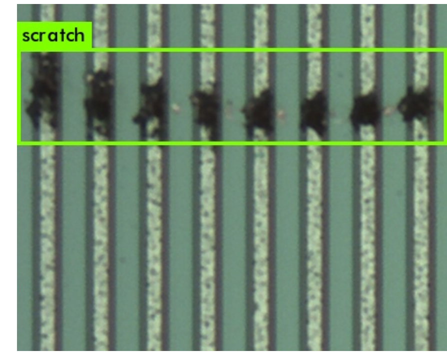


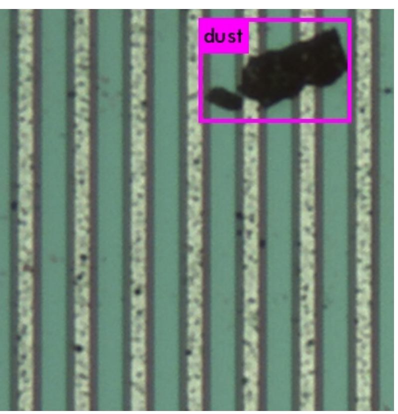
Defect Classification

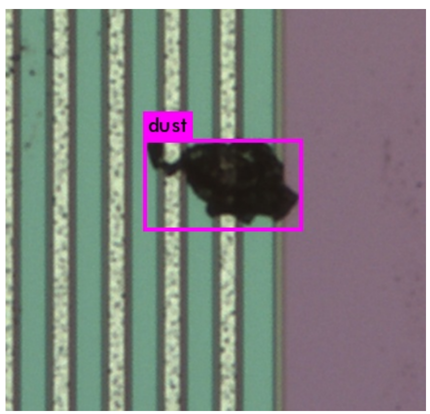


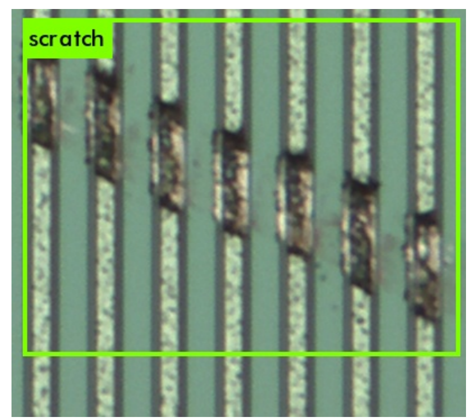


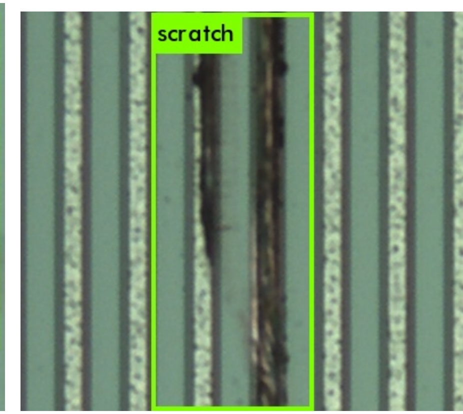












Summary

- Optical inspection and metrology setup to inspect different components of STS (not limited to)
- Inspection methods are constantly improving
- Analysis methods and tools are further improved and optimized
- Machine learning is a good addition to the inspection logic
- 25 sensors are inspected
- More sensors -> further improvement