



# Status update on ACF interconnect tests at UniGE

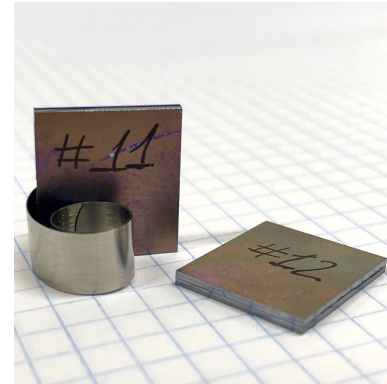
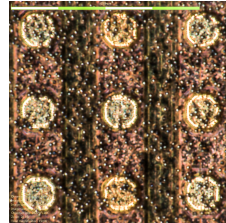
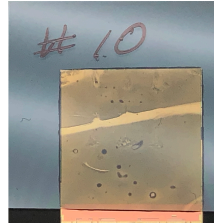
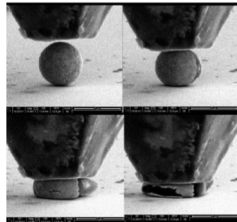
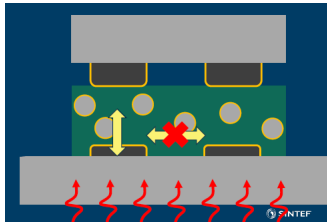
**CLICdp vertex & tracking  
WG meeting 21/06/2019**

**Mateus Vicente (EP-LCD)**  
+ Mathieu B. + Dominik D. + Helge Kristiansen (Conpart) + Molly Strimbec (Conpart)

# Remainder

## Anisotropic Conductive Film (ACF)

- **18  $\mu\text{m}$  adhesive film filled with 3  $\mu\text{m}$  conductive micro-particles**
  - Curing starts at  $\sim 100^\circ\text{C}$
  - Recommended bonding temperature =  $150\text{-}180^\circ\text{C}$ 
    - ACF-63: Ni/polymer – Film with high density of particles
    - ACF-64: Au/Ni/polymer – Film with lower particle density
  - Pre-bonding: 10 kg at  $80^\circ\text{C}$  during 10 seconds
  - Bonding with **100 kg** force
    - Film flow at  $80^\circ\text{C}$   $T_{\text{flow}}$  seconds and final film curing at  $150^\circ\text{C}$  for 18 s
- S10: Timepix-Glass, ACF-63 +  $T_{\text{flow}} = 100\text{s}$
- S16: Timepix-Glass, ACF-64 +  $T_{\text{flow}} = 500\text{s}$   
(New)
- S11: Timepix-Timepix, ACF-63,  $T_{\text{flow}} = 100\text{s}$
- S12: Timepix-Timepix, ACF-64,  $T_{\text{flow}} = 100\text{s}$

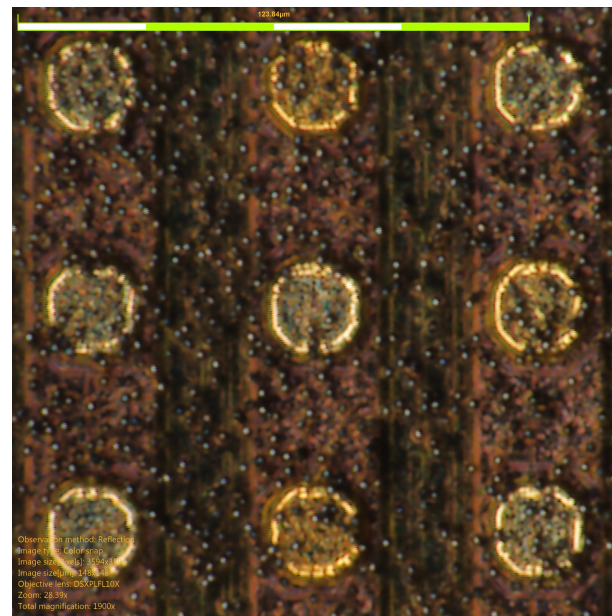
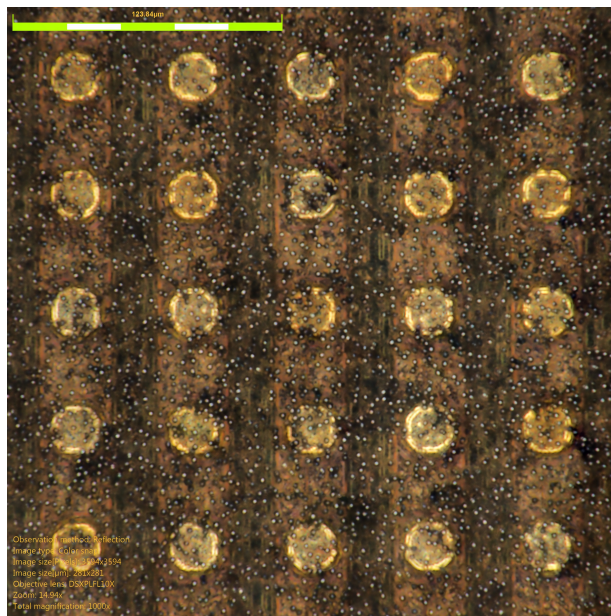
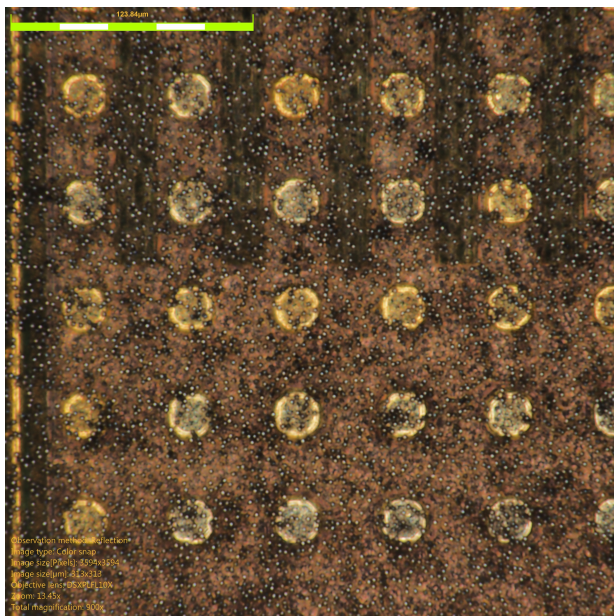




# First look

## Sample 10 – ACF 63 – Flow for 100s

- Initial (human) visual inspection shows about  $\sim 10$  particles per pixel pad





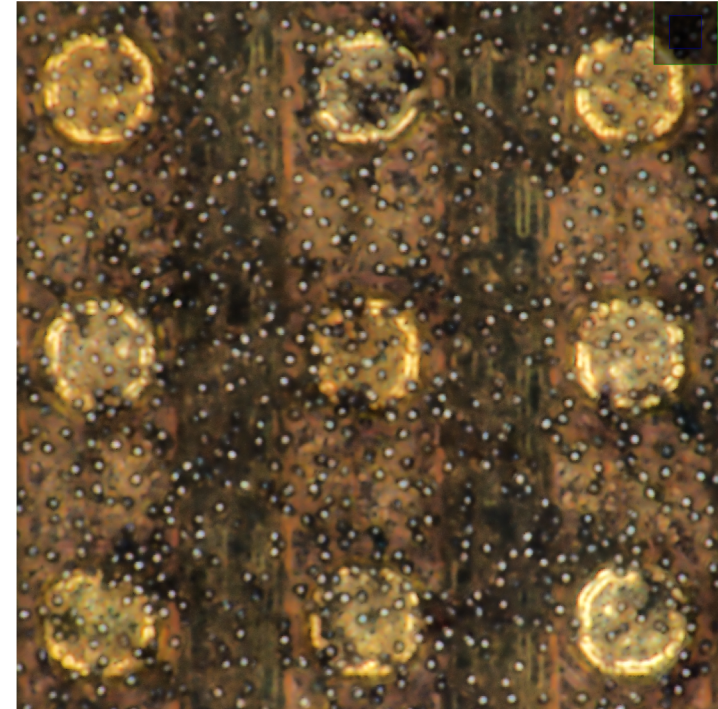
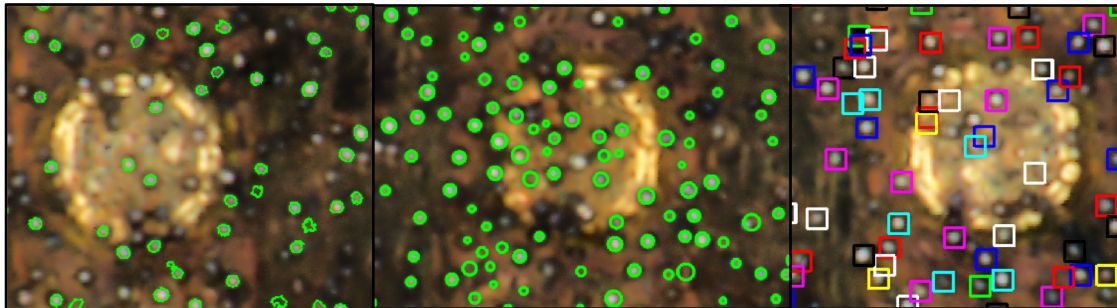


# Particle counting

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mvicente@cern.ch – 21/06/19

- Counting the conductive particles with computer vision using [OpenCV](#)
  - ▣ Finding contours
  - ▣ Blob detection
    - RGB to HSL color space conversion
  - ▣ Pattern matching
    - Averaged result + blob detection
    - Pattern matching  $\wedge^2$
  - ▣ Deep Neural Networks (new dnn OpenCV module)

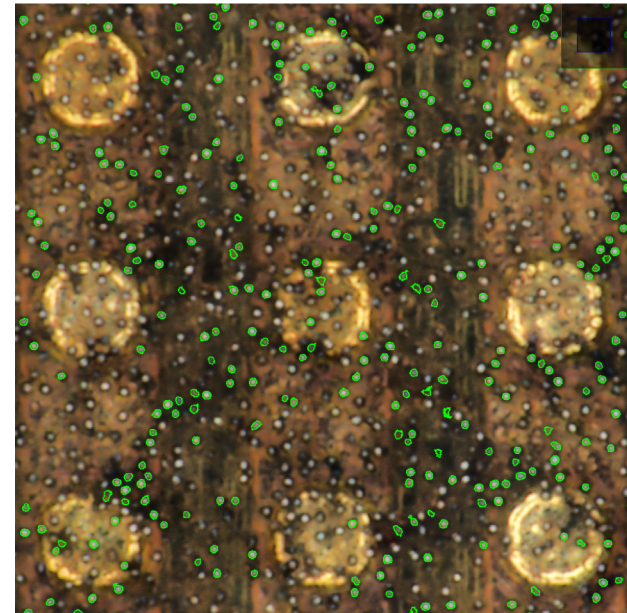
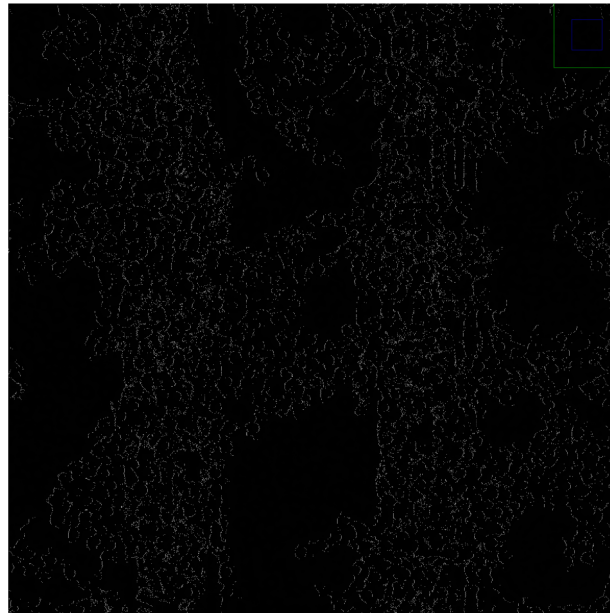
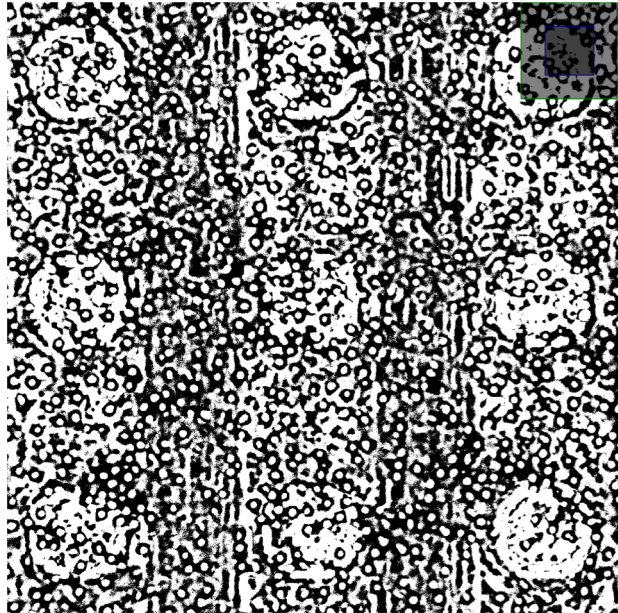




# Particle counting

## Finding contours

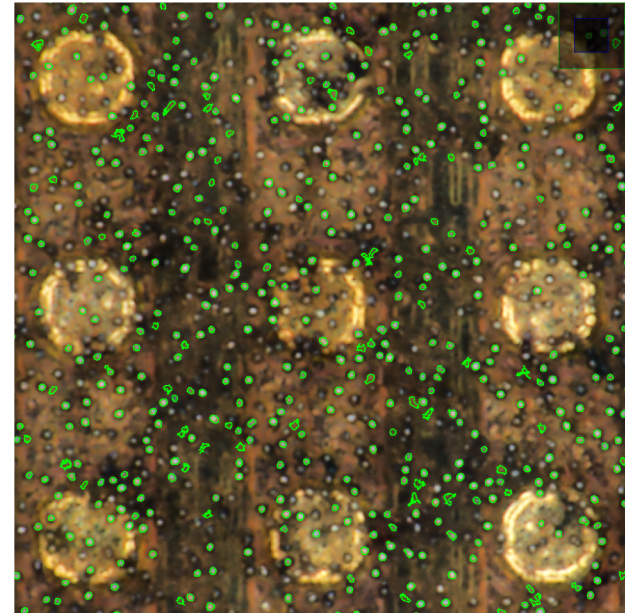
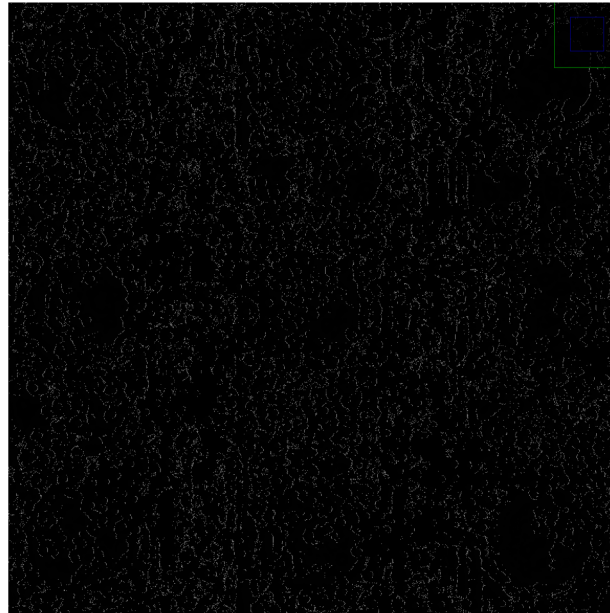
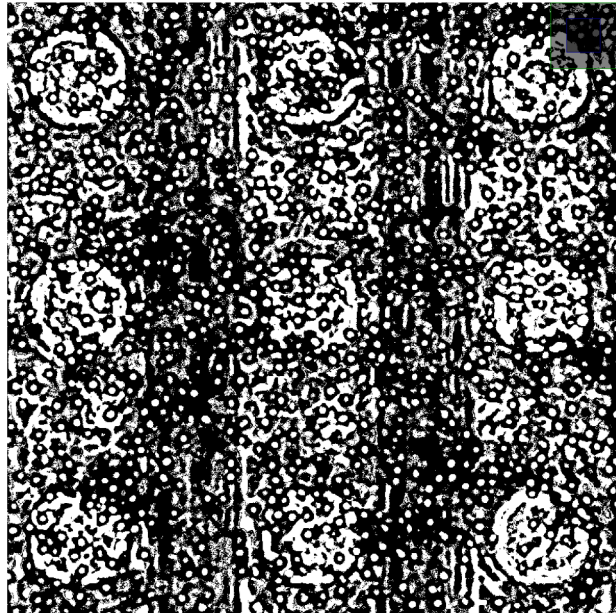
- Many methods start with converting the image into a binary image by applying different thresholds
- Contours are any 2 subsequent points  $(x_1, y_1)$  and  $(x_2, y_2)$  having same color or intensity



# Particle counting

## Finding contours

- Methods can profit from post-processing in the microscope pictures, such as contrast and brightness adjustment
- Contours detected  $\sim 70k$ ; Filtered out (by area, convexity, and etc) particle contours  $\sim 1000$

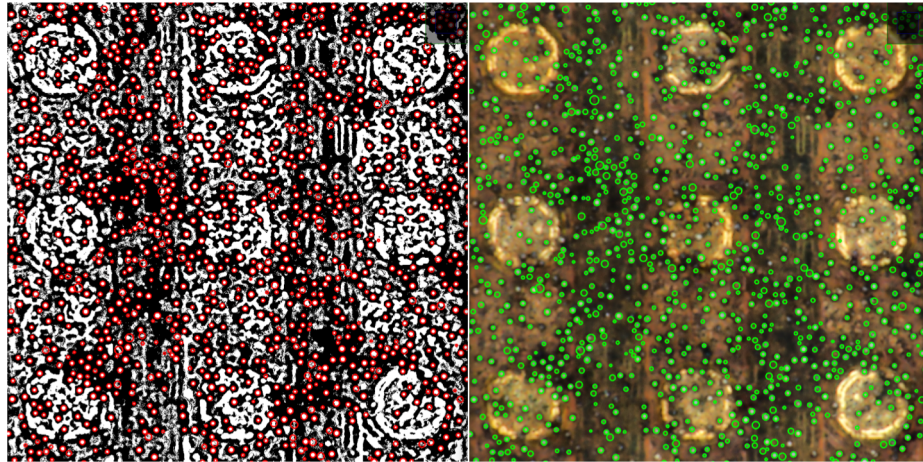




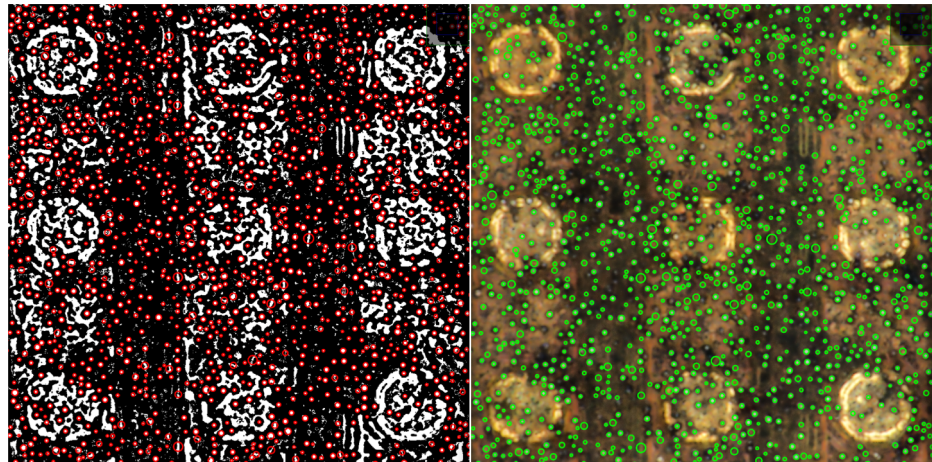
# Particle counting

## Blob detection

- A blob is a group of connected pixels in an image that share some common property, as the grayscale value
- As with the contour detection, it is also possible to filter out detected blobs
- Number of real and fake particles detected changes a lot with threshold and filter settings



**Default contrast and brightness**



**Higher contrast and lower brightness**

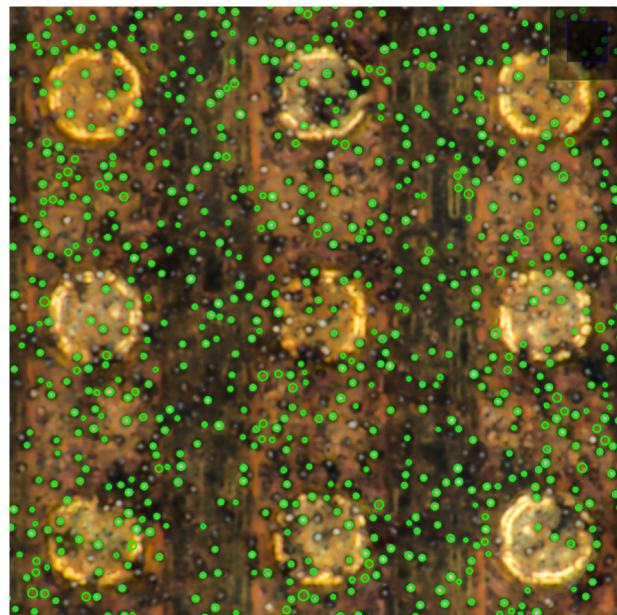
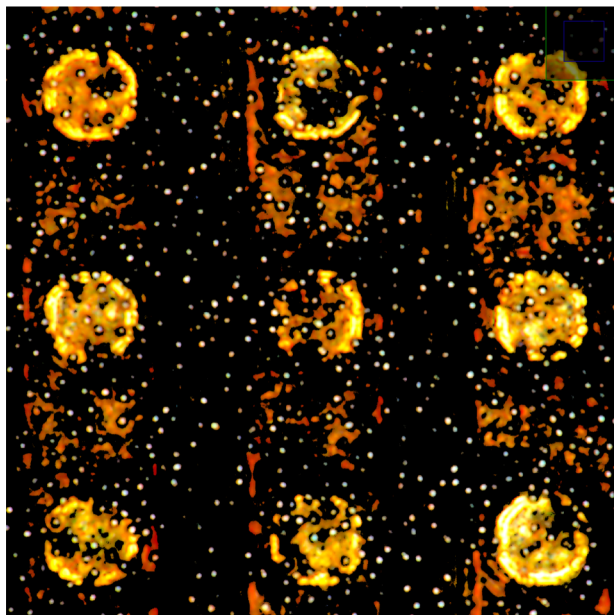
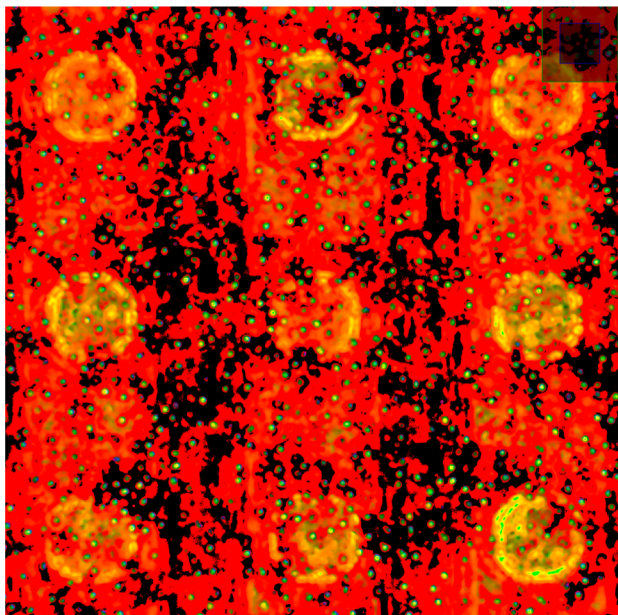




# Particle counting

## Blob detection in HSL

- Post-processing contrast and brightness also helps to highlight the particles
- Still, particles are lost on the cut and residual background yields fake detection

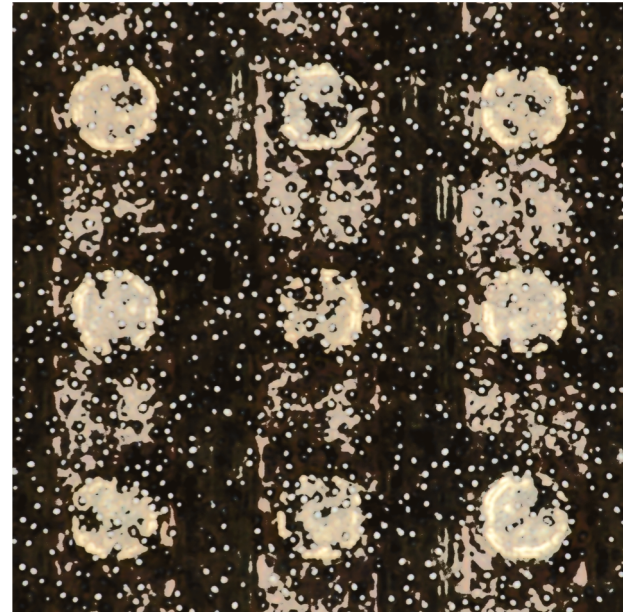
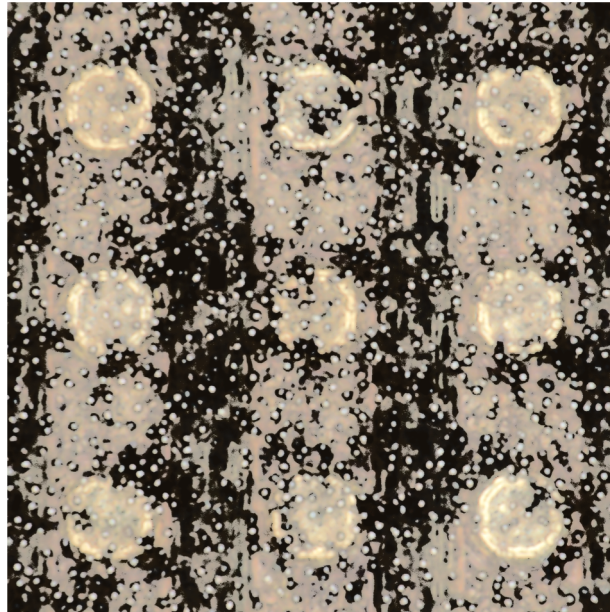
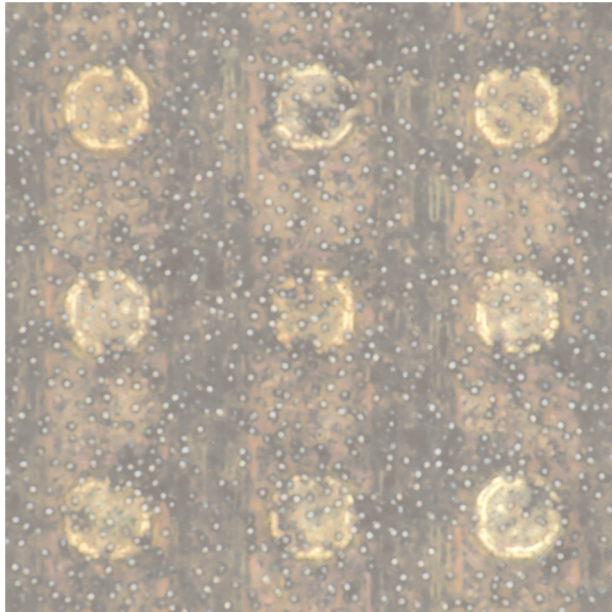




# Particle counting

## Problem looking for particles

- As different thresholds and filters are applied to the pictures, the non-uniformity (in shape and color) of different parts of the chip pictures creates false particle detections

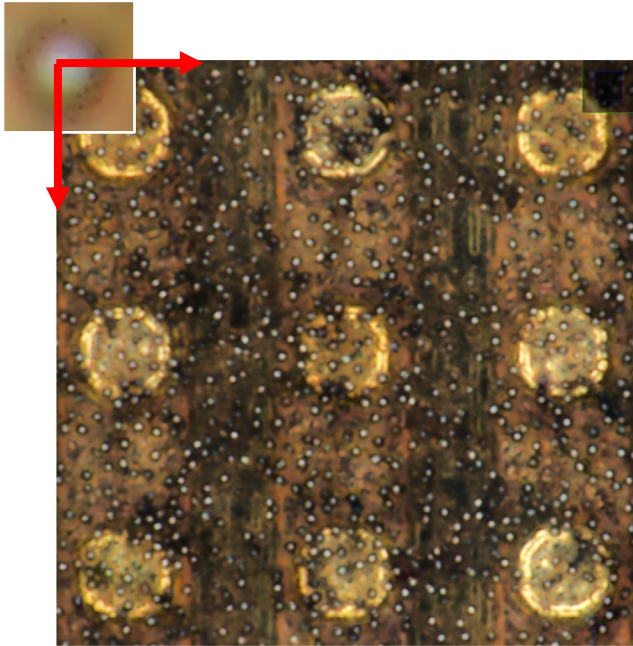




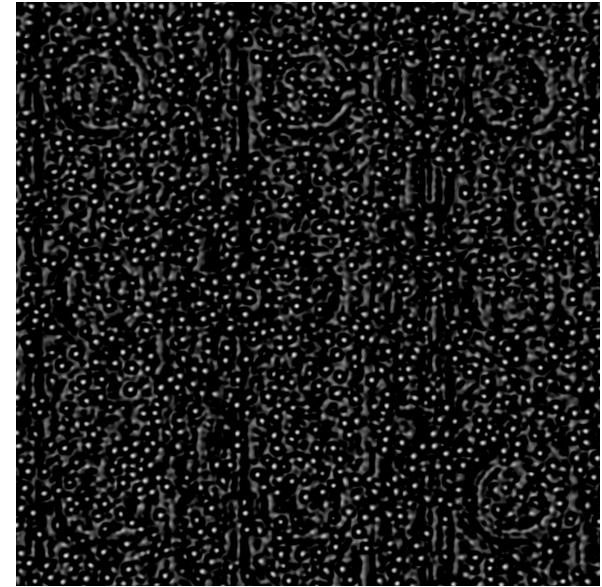
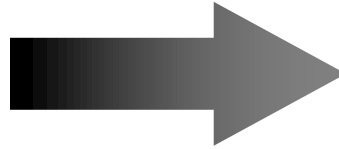
# Particle counting

## Pattern matching

- At each location, a metric is calculated representing how “good” or “bad” the match at that location is
- Pattern matching is limited to scale and rotation transformations



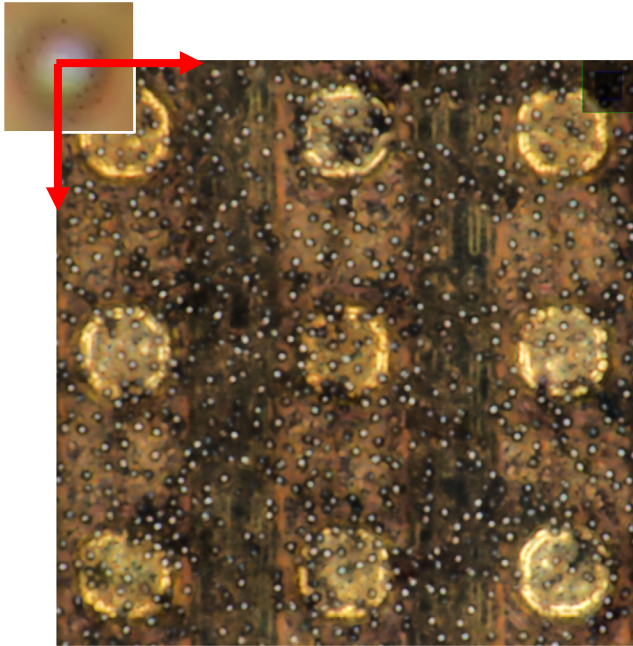
Pixel values goes from 0 to 1, where 1 is the perfect match



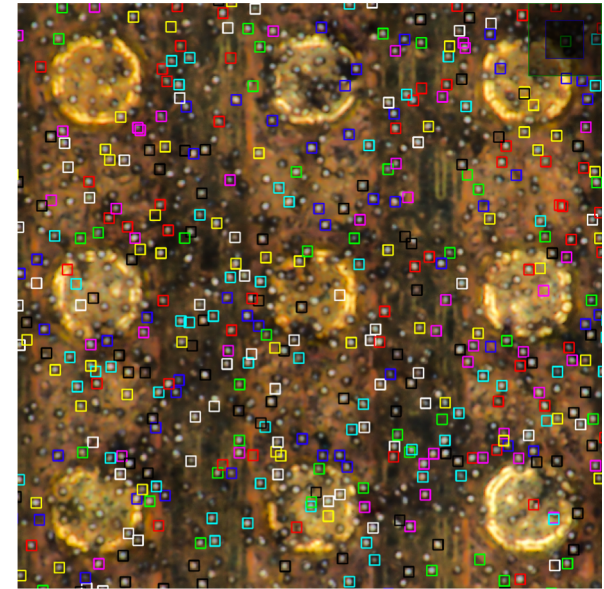
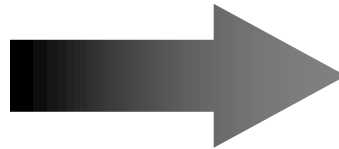
# Particle counting

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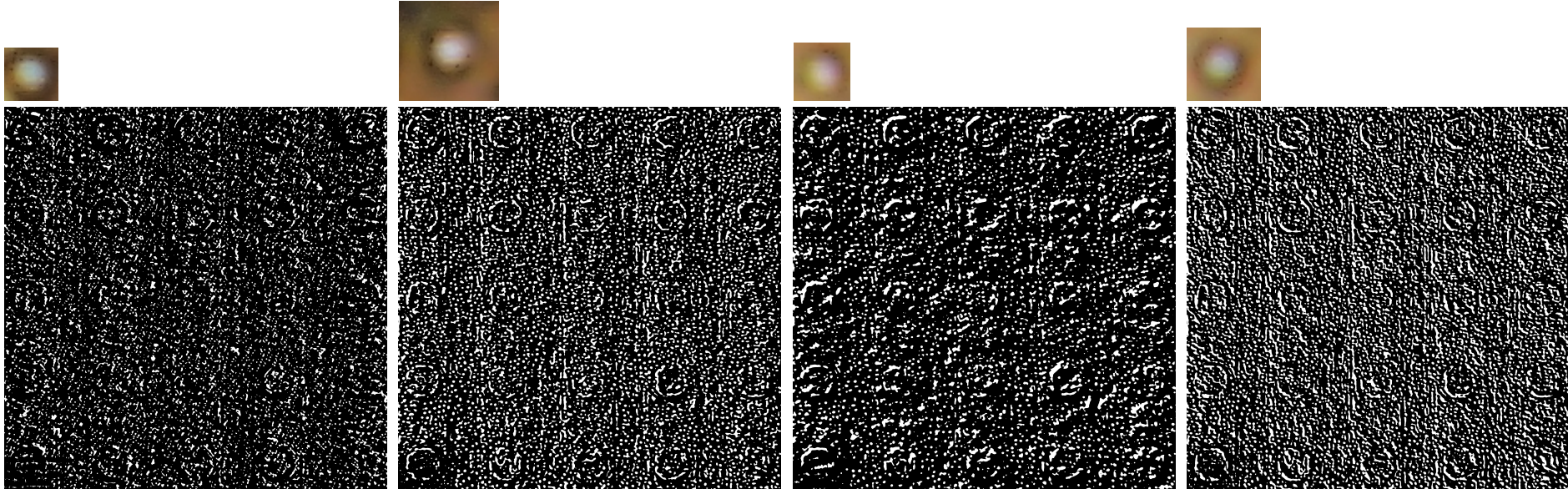
Good... less fake detections... still many particles missing



# Particle counting

## Pattern matching - Averaging the result matrix

- Each pattern will result in a different matching result matrix
- With the particles always in the same position, the “contamination” can be averaged out, leaving the particle **blobs**

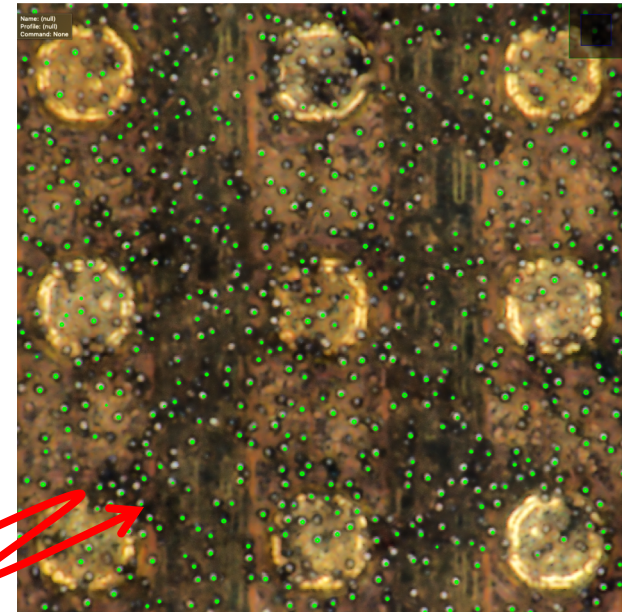
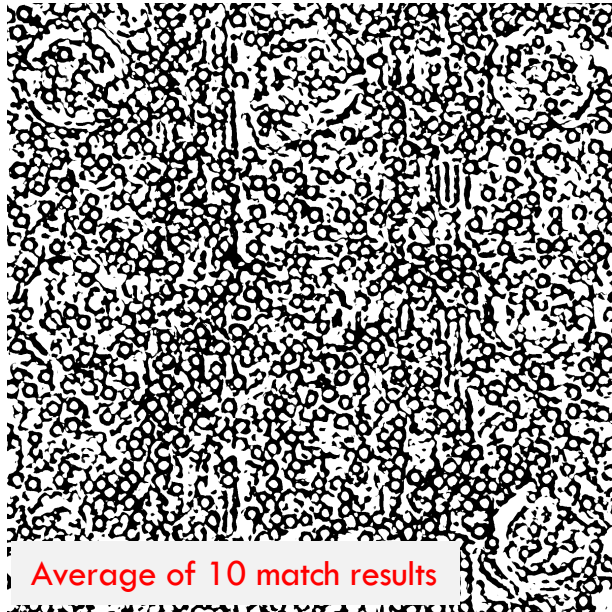




# Particle counting

## Pattern matching - Averaging the result matrix

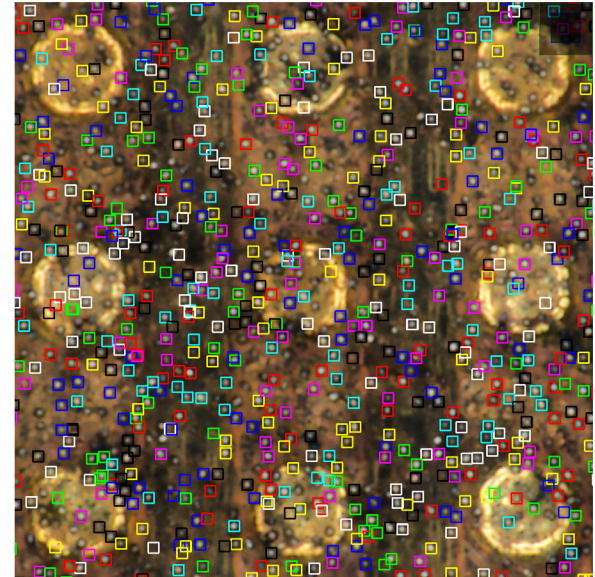
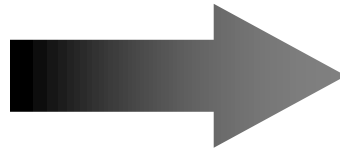
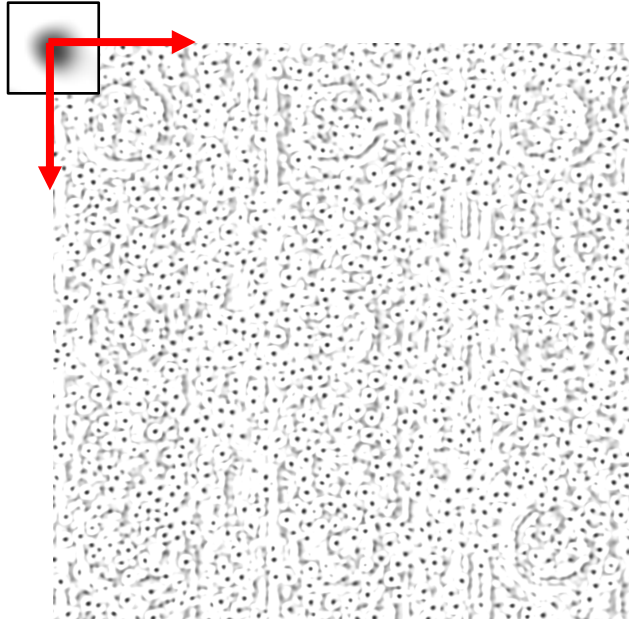
- Many particles are lost in the process
- No fake particle detection



# Particle counting

## Pattern matching on the pattern match result

- Match result shows particle blobs very isolated from each other
- Running a pattern match a second time helps to discover many more particles with almost no fake detection

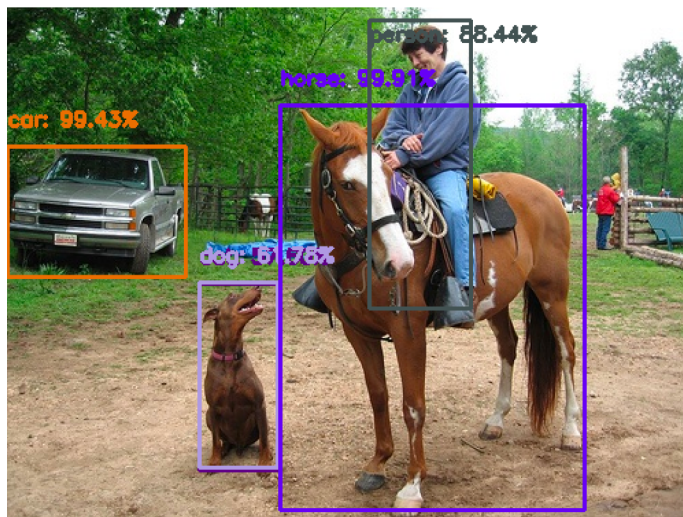




# Particle counting

## Deep Neural Networks and OpenCV

- New OpenCV module offers easy access to several **dnn** frameworks and layer types
- Running tutorials using the Caffe framework with an model trained on the COCO dataset (Common Objects in Context)
  - ▣ Capable of detect 20 objects in images, among: airplanes, bicycles, birds, boats, cars, cats, chairs, horses, motorbikes, people, potted plants, etc...

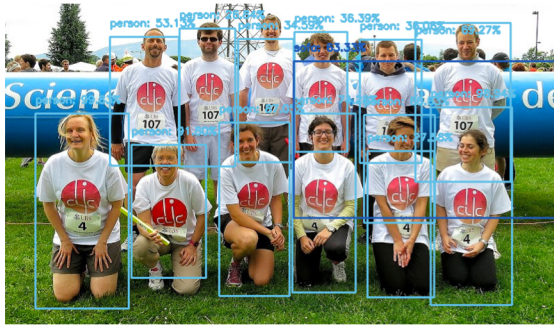


# Particle counting

## Deep Neural Networks and OpenCV

- Next step is to train a model with the patterns matched using the previous methods

Testing with custom pictures



Particles templates for dnn training

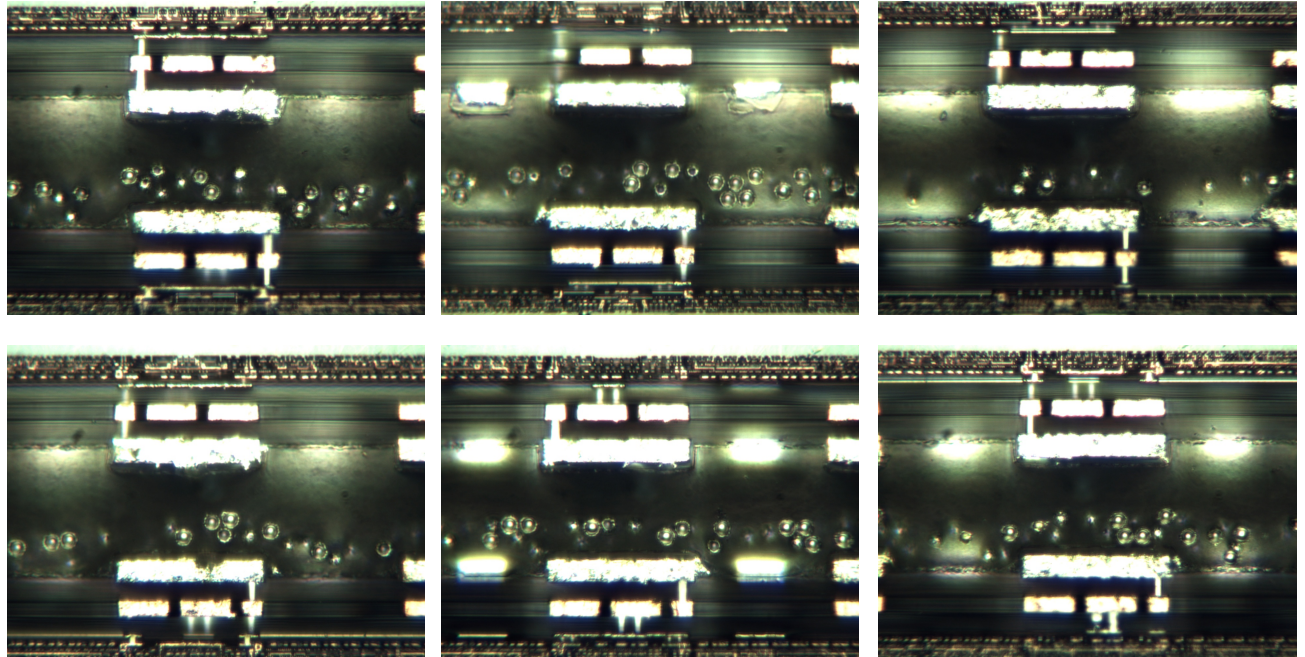




# Cross-section measurements

## Timepix-to-Timepix assemblies

- **S11**, high density film
- Good capture rate per pad
- Pictures shows no particle being crushed
- Pixel pad gap  $\sim 18 \mu\text{m}$ 
  - ▣ Good agreement with film thickness
  - ▣ Thinner film needed for next assemblies;



# Cross-section measurements

## Timepix-to-Timepix assemblies

- **S12**, low density film
- Low particle capture rate
  - ▣ Confirming surface pictures
- No crushed particles
- Smaller pixel gap  $\sim 6 \mu\text{m}$

