



LEAPS Integrated Platform Workshop

11-12 May 2021
Zoom
Europe/Zurich timezone



Real-time beam detection and tracking from pinhole imaging system based on computer vision with TensorFlow.

Andriy Nosych (ALBA-CELLS, Spain)

Target: automated beam diagnostics routine for pinhole operation

Rockets are machines, but so far they went to space not because of Machine Learning.

Rockets go to space thanks to precise models.

Precise models beat good statistics!

Particle accelerators are also precise machines.
ML is not very common here yet, more auxiliary.

Common ML applications in accelerators:

- Design + performance optimization
- Anomaly detection
- Fault prediction
- Models from data

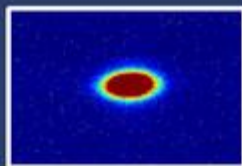
What about accelerator diagnostics and beam dynamics?
Not easy to find an application!



Alba machine status screen: you can always see beam image from a pinhole camera



Current
201.56 mA



Size (1σ)
H = 58.9 μm
V = 31.6 μm

Orbit
(RMS)
H = 0.048 μm
V = 0.034 μm

Beam for BLs

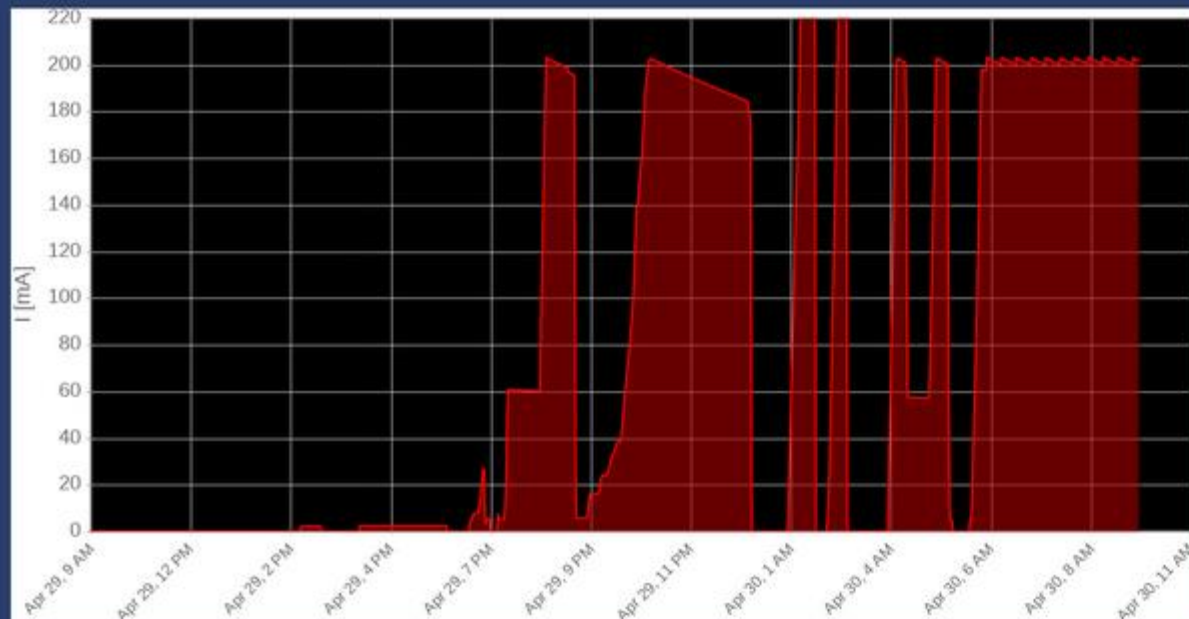
Time to inject: 00:08:32

Operation mode
Top-up Mode

Lifetime
21h 54m

Avg. pressure
3.8e-10 mbar

Current x lifetime
4419 mAh

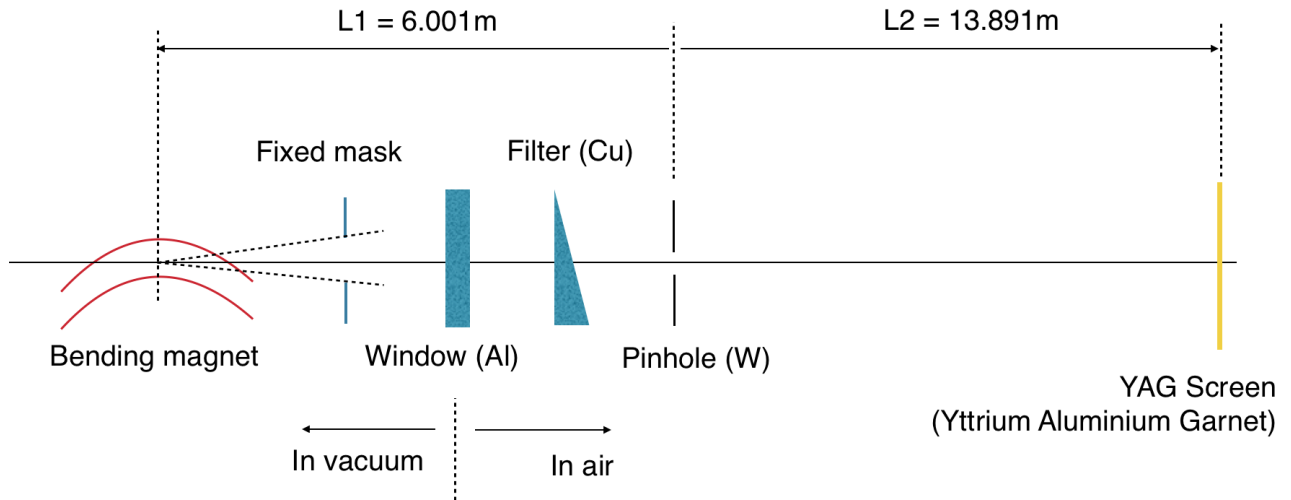


Beamline Status		ID Gap
BL01	MIRAS	23.11 mm
BL04	MSPD	B = 2.10 T
BL09	MISTRAL	
BL11	NCD-SWEET	6.00 mm
BL13	XALOC	6.00 mm
BL22	CLAESS	13.00 mm
BL24	CIRCE	30.00 mm
BL29	BOREAS	30.00 mm

Message from CR:

Tuesday 30-Apr-2019 09:52:58

Pinhole camera system at Alba Synchrotron



X-ray pinhole camera provides transverse size measurements of the electron beam:

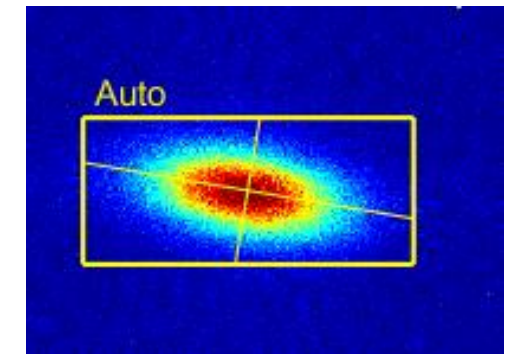
$$\sigma_{\text{YAG}} = (L_2/L_1) \sigma_{\text{source}}$$

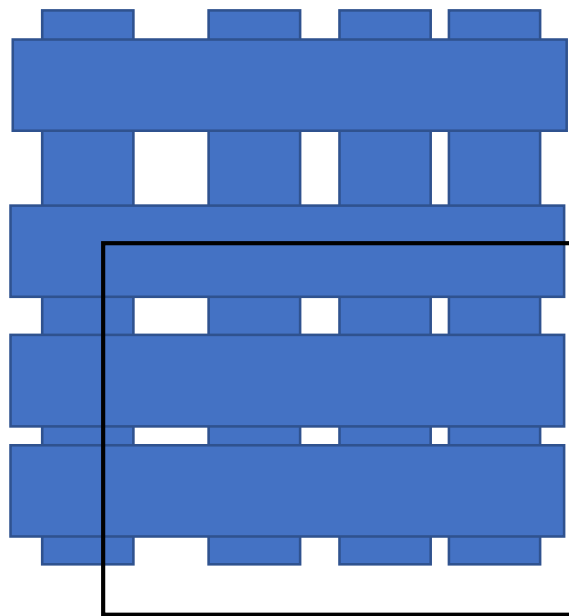
$$\sigma_{\text{YAG}}^2 = (X\sigma_b)^2 + (\sigma_{\text{PSF}})^2$$

$$\sigma_{\text{PSF}} = \sqrt{\sigma_{\text{blur}}^2 + \sigma_{\text{DIFF}}^2 + \sigma_{\text{screen}}^2}$$

$$\sigma_{\text{diff}} = \frac{\sqrt{12} \lambda L_2}{4\pi w}$$

$$\sigma_{\text{blur}} = \frac{w(L_1 + L_2)}{\sqrt{12}L_1}$$





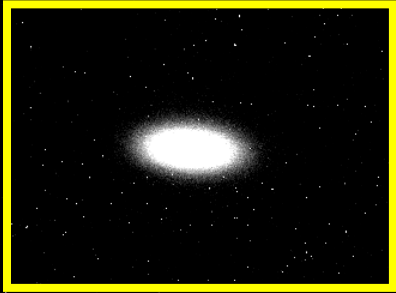
100x100 μm

out of view
50x100 μm

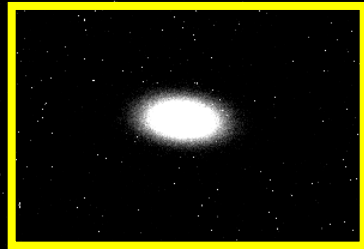
10x100 μm

Pinhole CCD Field of View

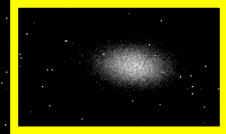
100x50 μm



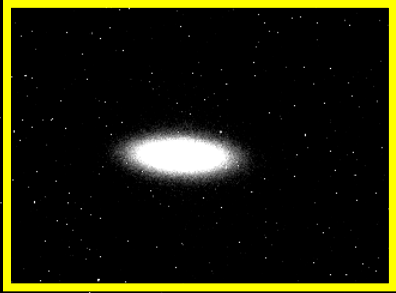
50x50 μm



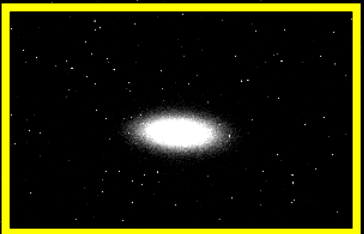
10x50 μm



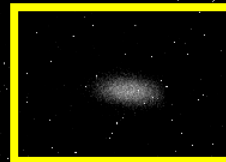
100x10 μm



50x10 μm



10x10 μm



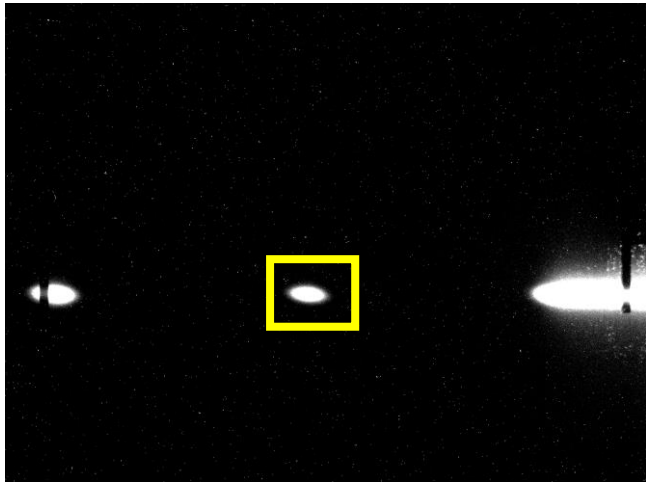
At Alba there are actually 2 pinhole systems, both able to see up to 6 beam images at a time

Each beam image has different

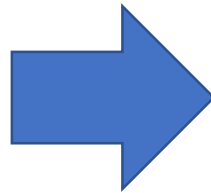
- source pinhole H&V size
- point spread function
- ROI centered around it

Beam spot parameters are manually fixed for fitting

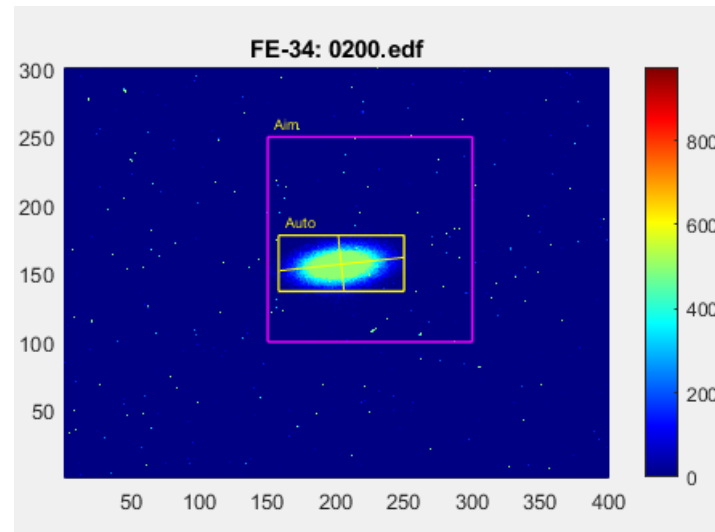
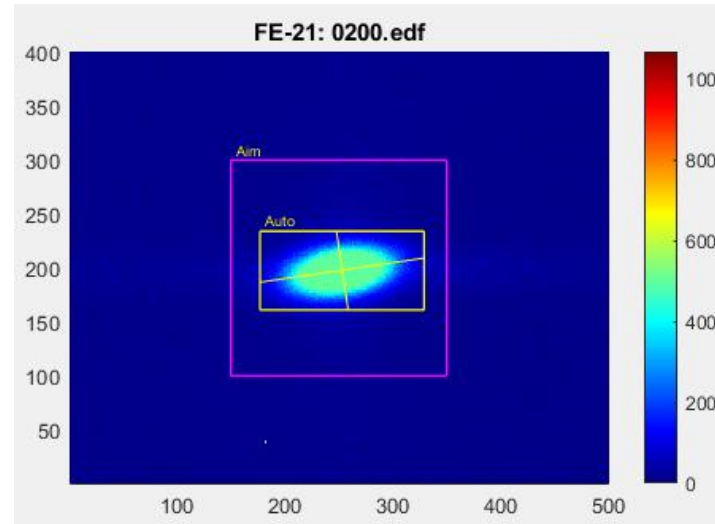
We have to tell the system where to look (ROI), and hope the conditions won't change (e.g. beam moves out or pinhole motors are moved for experiments)



3Hz refresh rate to control system

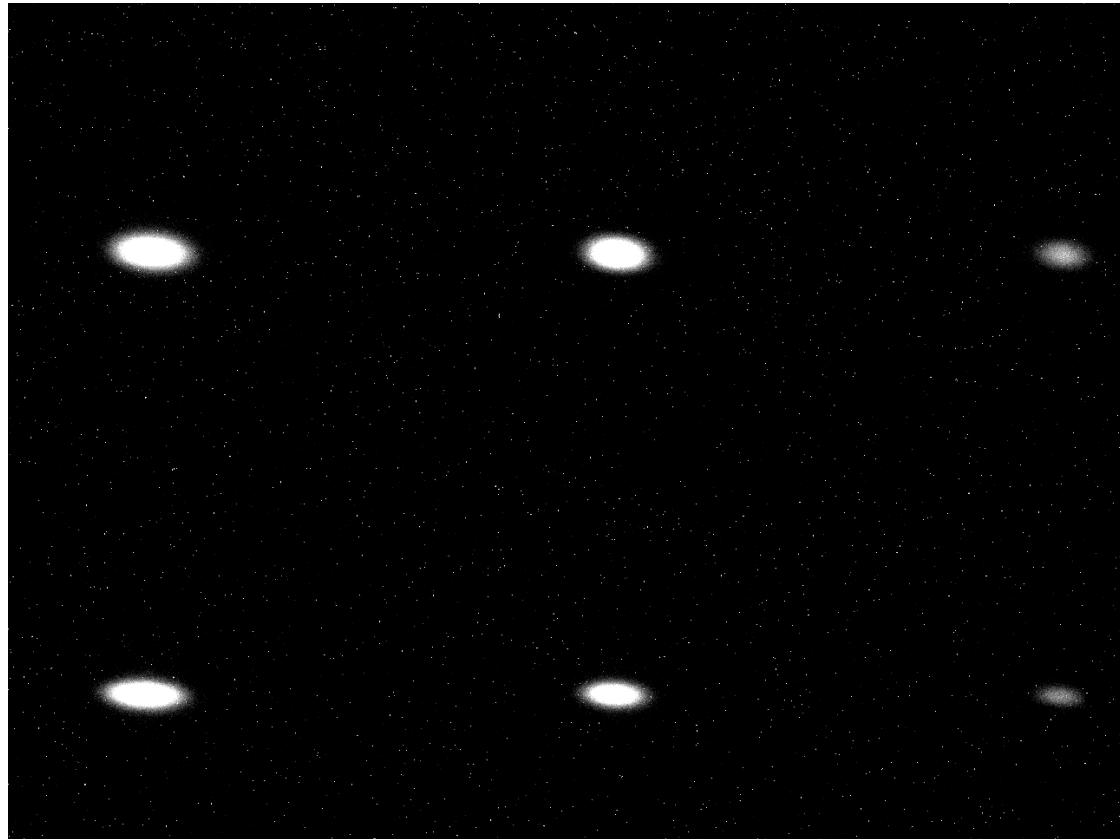


Math analysis within ROIs of both pinholes



==== FE-21 ====	==== FE-34 ====
filename: 0086.edf	filename: 0086.edf
Amp = 1074.42	Amp = 970.28
Bkg = 22.0649	Bkg = 0.0000
$X_0 = 254.14$ [px]	$X_0 = 203.57$ [px]
$Y_0 = 198.29$ [px]	$Y_0 = 156.72$ [px]
$X_0 = 466.38$ [um]	$X_0 = 594.48$ [um]
$Y_0 = 323.34$ [um]	$Y_0 = 460.78$ [um]
σ_X (2D) = 56.23 [um]	σ_X (2D) = 55.21 [um]
σ_Y (2D) = 22.33 [um]	σ_Y (2D) = 23.10 [um]
σ_X (2D) = 30.72 [px]	σ_X (2D) = 19.04 [px]
σ_Y (2D) = 13.92 [px]	σ_Y (2D) = 8.16 [px]
σ_X (1D) = 55.61 [um]	σ_X (1D) = 52.98 [um]
σ_Y (1D) = 23.61 [um]	σ_Y (1D) = 23.03 [um]
tilt = 0.147 [rad]	tilt = 0.109 [rad]
tilt = 8.4 [deg]	tilt = 6.2 [deg]
$\epsilon_H = 5.2985$	$\epsilon_H = 3.6421$
$\epsilon_V = 0.0219$	$\epsilon_V = 0.0197$
K = 0.41 [%]	K = 0.54 [%]
Int _{px} = 25.38	Int _{px} = 9.17
Err _H 1D = 197.85	Err _H 1D = 595.05
Err _V 1D = 1182.07	Err _V 1D = 568.26
Err 2D = 4.51e+06	Err 2D = 6.08e+06

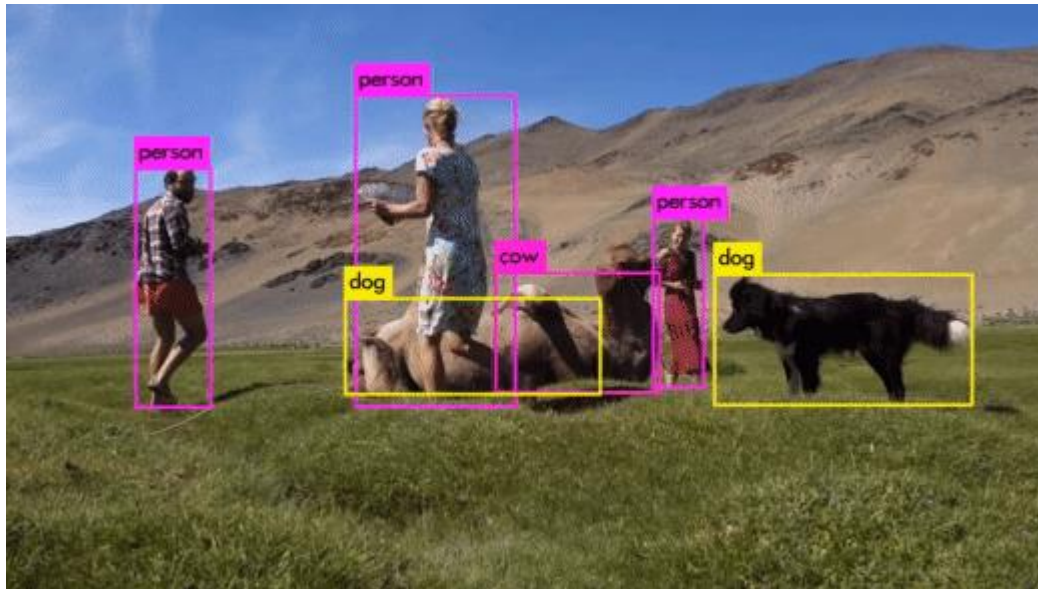
What if there was an automatic system that looks at this image, knows what is what, and what fit parameters to use?



Selecting a ML technique

Structure: Computer vision

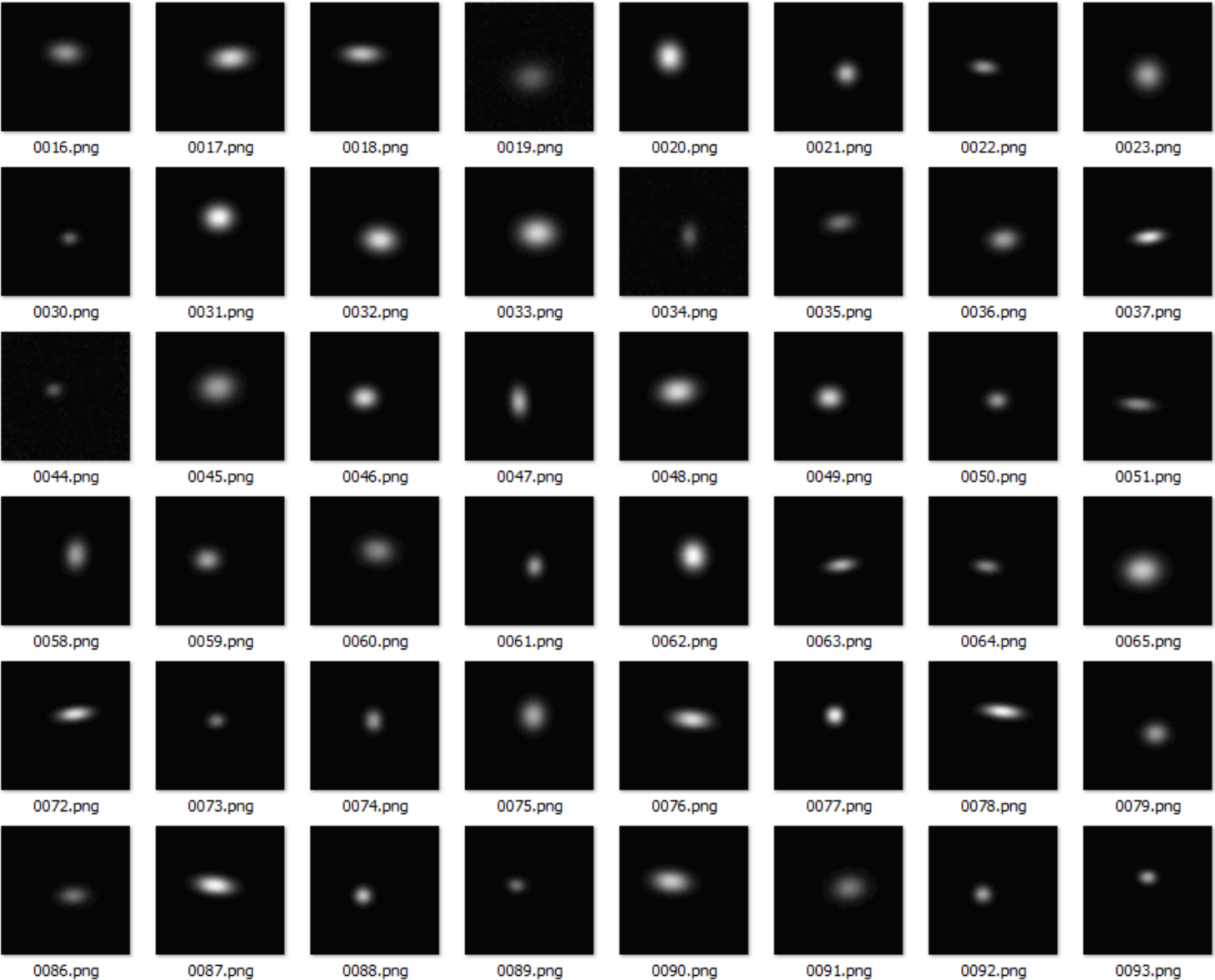
- Learning: **Supervised**
 - Task: **Classification**
 - Architecture: **ImageAI with Tensorflow2.4 backend** [<https://imageai.readthedocs.io>]
 - Algorithm: **YOLOv3** [<https://pjreddie.com/darknet/yolo/>]



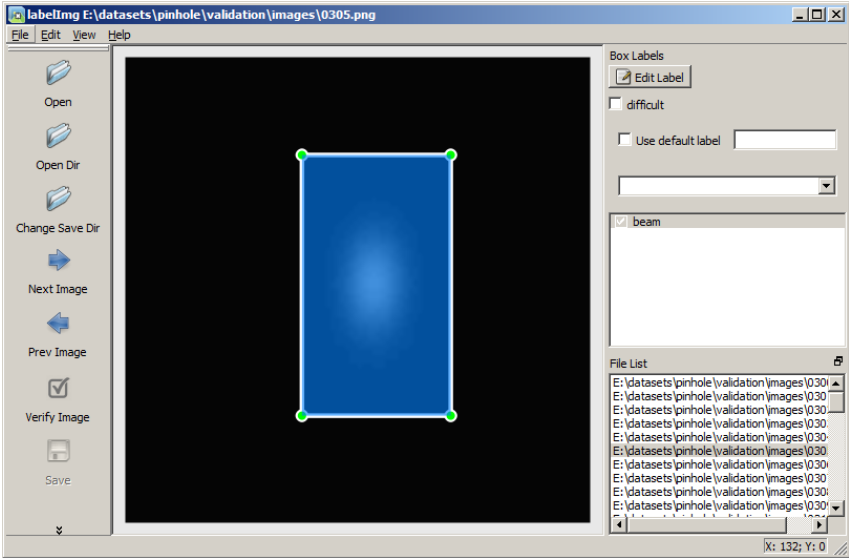
YOLO: You Only Look Once

A real-time object detection system, based on convolutional NN which looks at the whole image and predicts bounding boxes with classifiers

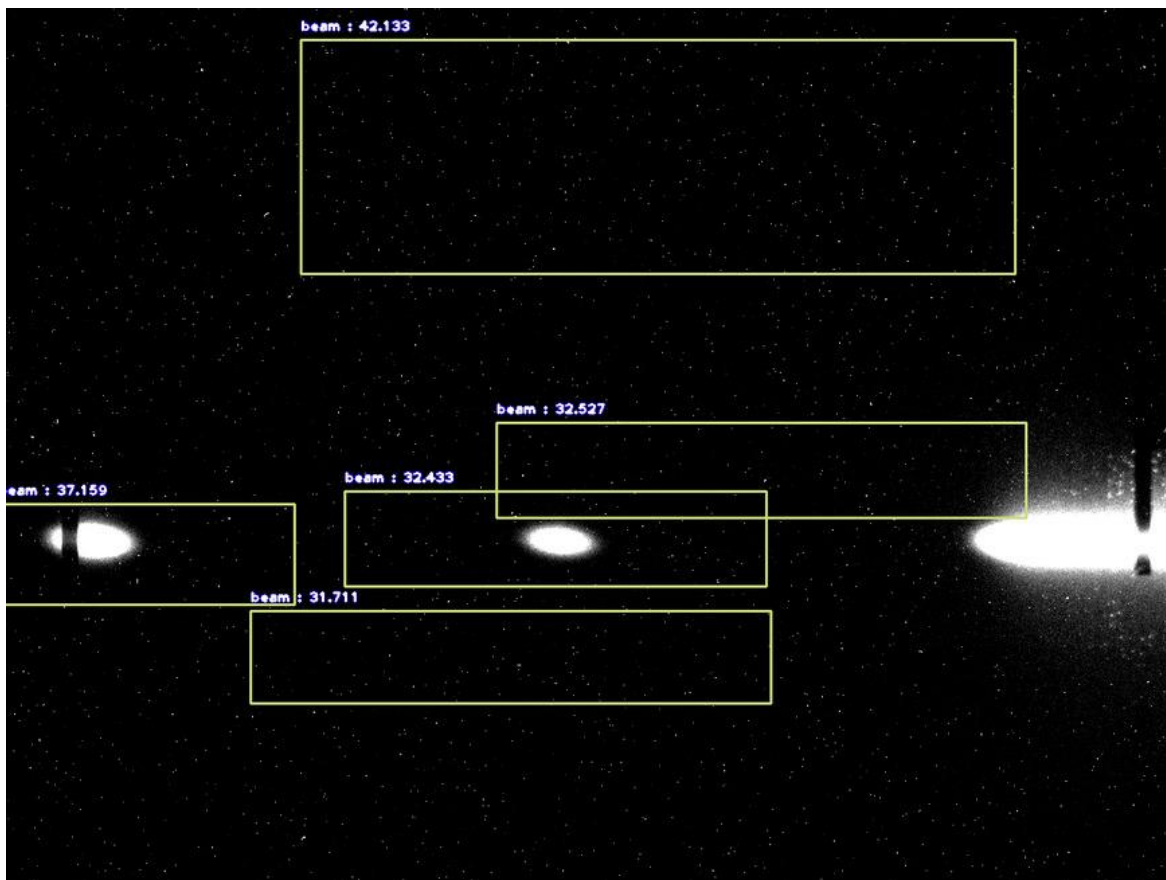
Models trained on 200-1000 randomly generated Gaussians with annotations



Annotations automatically generated and verified with labellmg.py



When learning goes wrong



8 epochs

1000 training images 72x72 px

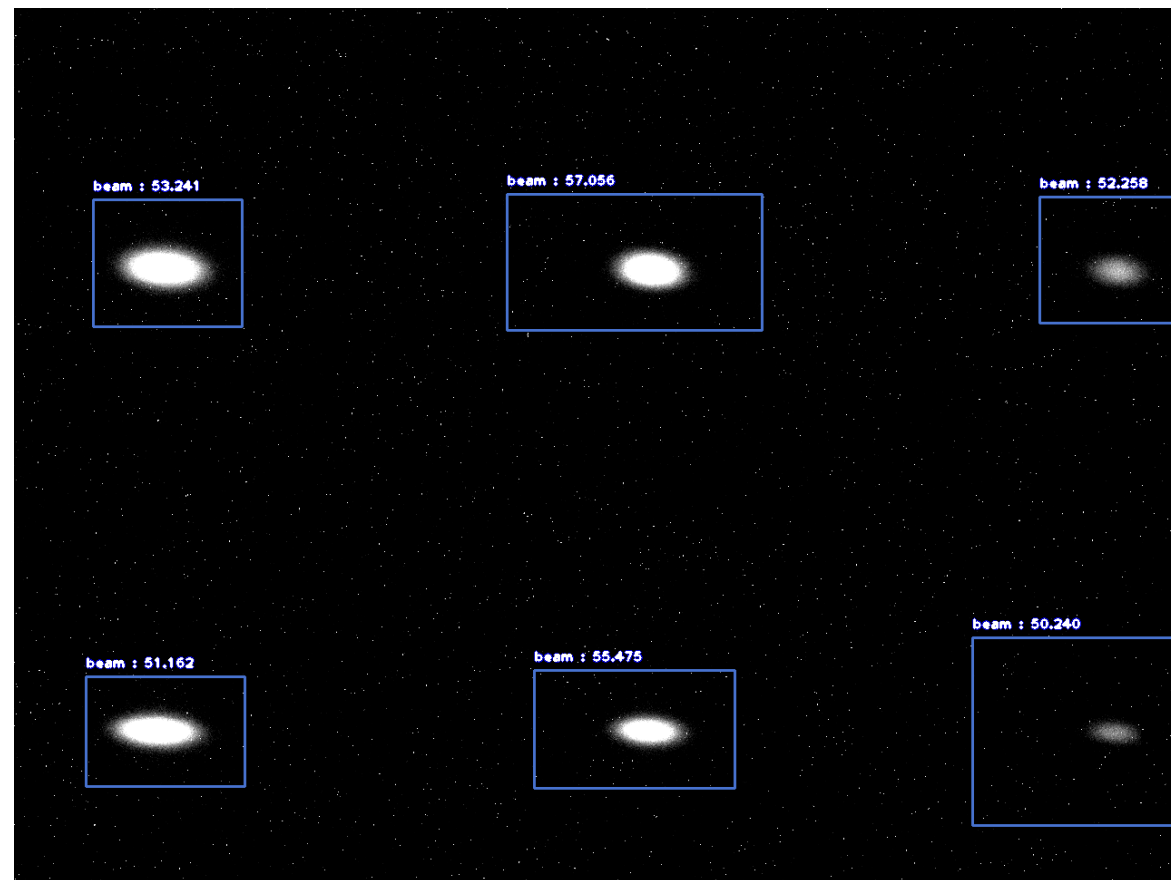
Time of each epoch: 6h (3GHz CPU)

Wrong hyperparameters?

Not enough training epochs?

Insufficient/wrong learning data?

Exam passed



23 epochs

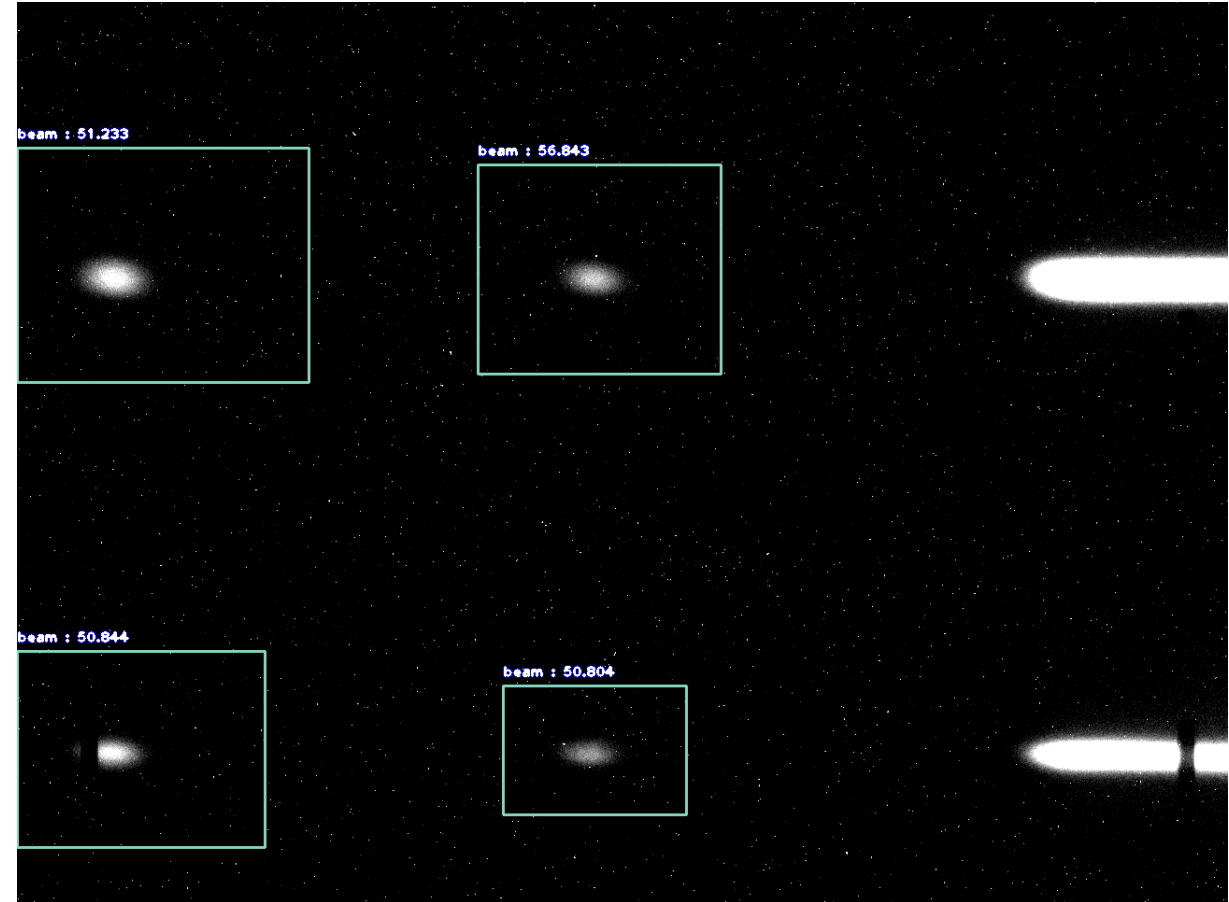
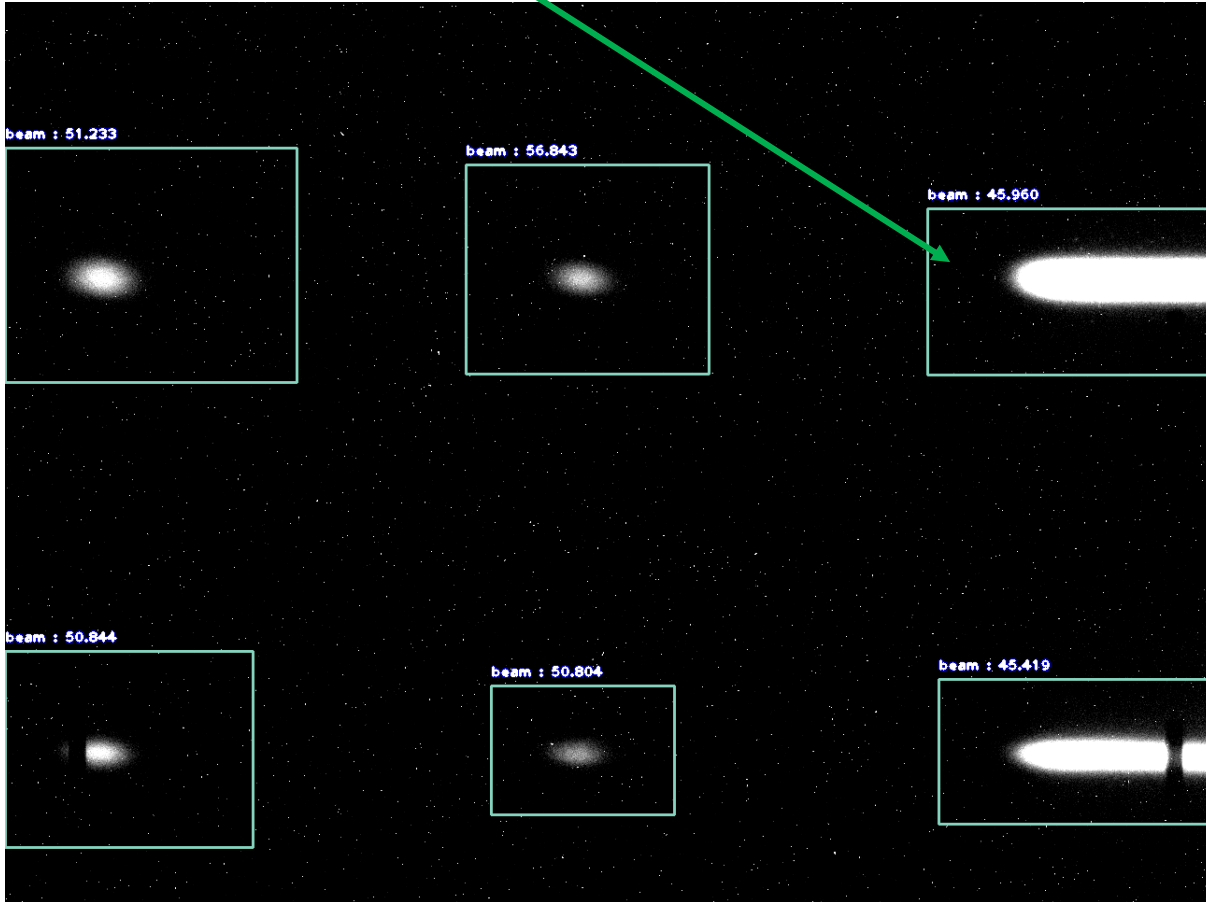
300 training images 100x100 px

Time of each epoch: 2h (3GHz CPU)

Model size: 250 Mb

A small detail

Residual beam fan: unusable. What to do with it?



- 1) Ignore using Confidence score threshold
- 2) Train NN on another object class "Fan" (not tested)

Acquisition at 1Hz (5x video speed up)



Current AAN performance:

1.6 FPS detection speed on a laptop

250 Mb model size

Trained on single object (“beam”)

Questions to ANN

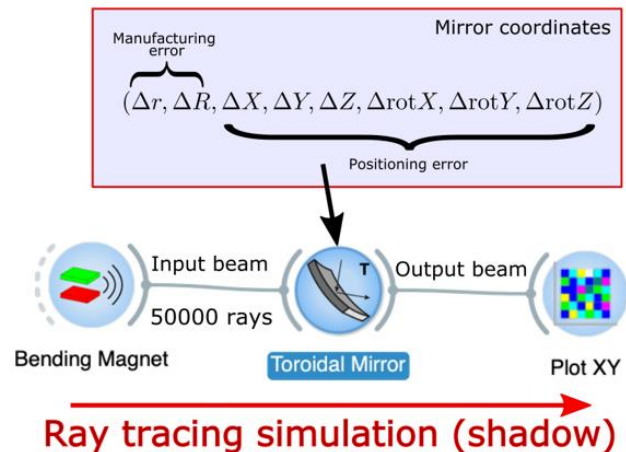
- How many Epochs do you really need?
- How to further optimize the confidence score?
- Better to train on “fan” object as well?
- ROI sometimes off, why?
- Can you detect faster?
- Can you have a smaller model size?

Other ML projects done at Alba Synchrotron

MINERVA Beamline (Dominique Heinis)

Machine learning to model the behavior of a mirror subjected to manufacturing errors and misalignments (scikit-learn)

- learning using linear model (with polynomial features) to take into account optical aberrations and nonlinearities
- model calculates quickly the output beam (based on tensor product instead of ray tracing)
- model can be used to retrieve an analytical formula
- model allows numerical optimization (can be easily integrated in a steepest gradient like method)
- for the moment just one optical element but there is no theoretical constraints to extent it to a complete beamline



Beam Physics (Zeus Marti, Emilio Morales)

ANN to solve the measured orbit response matrix fit to avoid using the model (TF, Keras).

It does not work, it has too many elements ($88 \times 120 \times 4$) and knobs (112) and is too non linear, the training data is huge. Instead it was possible to fit the inverse orbit response matrix, since it has much less elements (432) for the same number of knobs and it is much more linear. It turned out to be so linear that a simple linear fit behaves as well as an ANN for the present precision of our measurements.

Conclusions

If NN works - it's a huge advance.

Advantages to date:

All tools , tutorials, guides, libraries, algorithms are free.

Bottlenecks to date:

Large time investment to tune and train the model.

Large hardware investment.

Quantity matters (CPU->GPU->HPC).

Machine training is long
Machine thinking is hard
(Great opportunity for student projects)