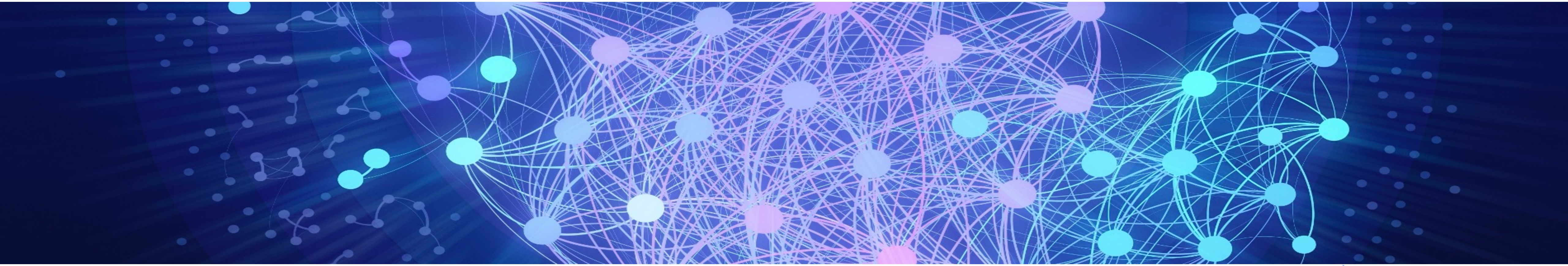
Automated Wing in Tank Inspection using AI:

Progress on a Proof of Concept project, towards Robotics and AI applied to Industrial Inspection

3rd Dec 2020 - iTalk

STFC-Hartree Centre

Jony Castagna



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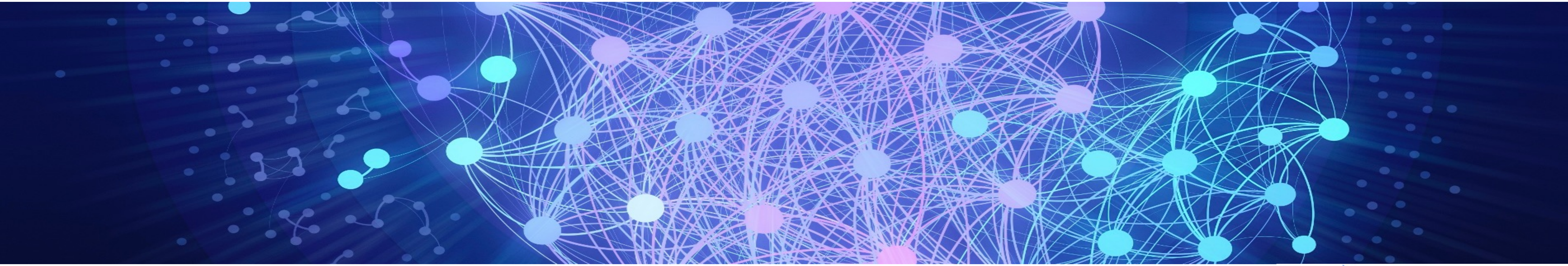
Overview

- The Challenge
- Phase I: the supervised learning approach
- Phase II: use of a DMU CAD model with semi-supervised approach
- Phase III: the unsupervised learning approach
- Conclusions and Future work



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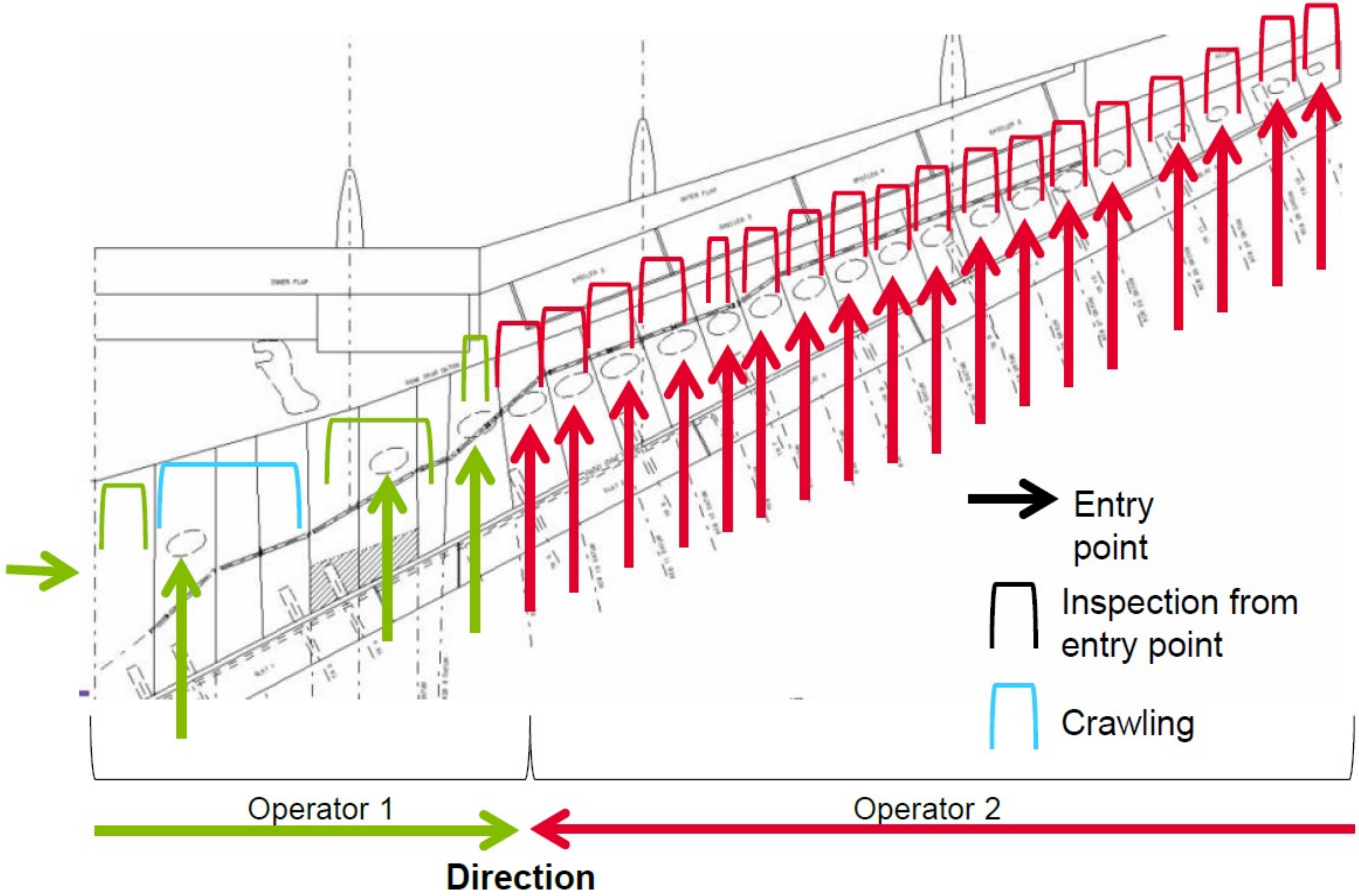


Challenge:

Wing Tank Inspection Process

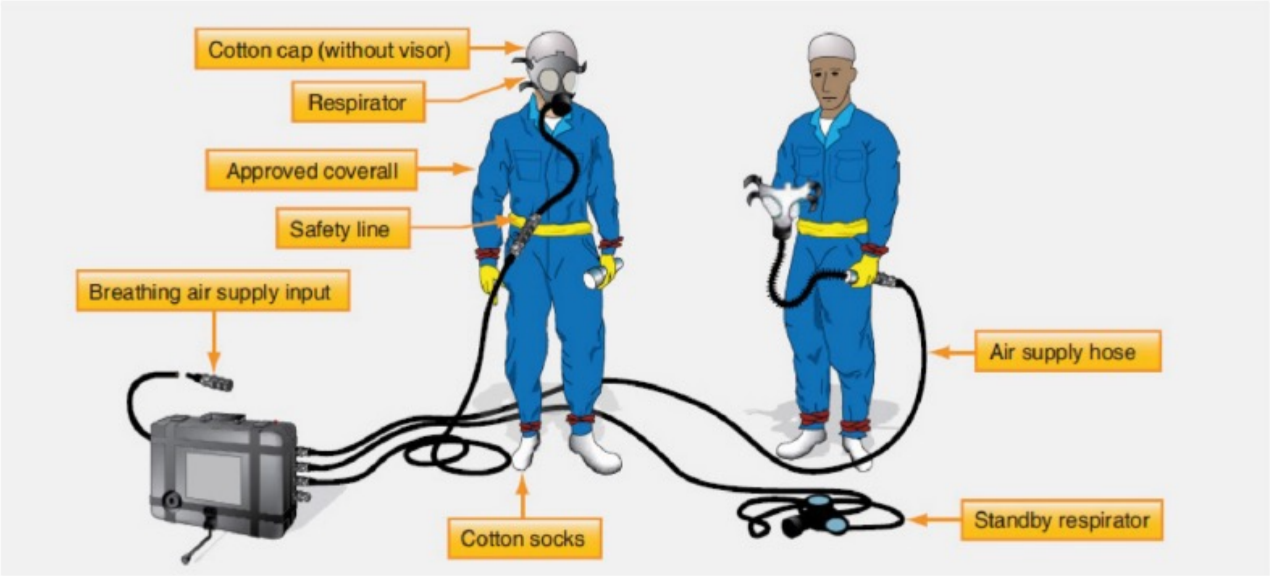
Visual quality inspection occurs at multiple build stages

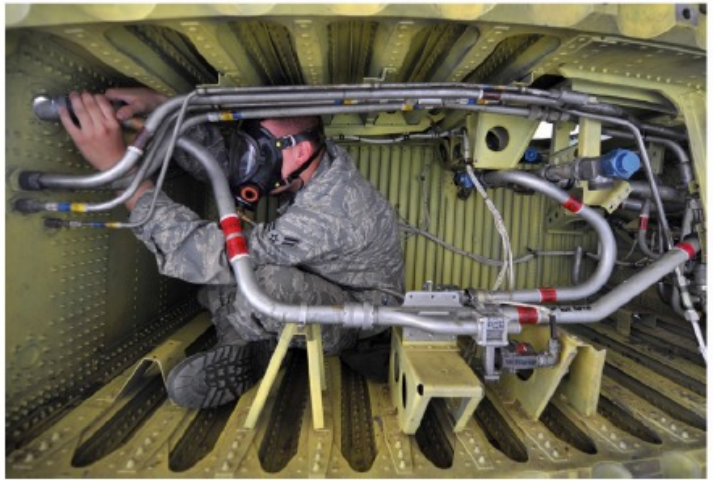
Two operators per shift per wing for the A320 aircraft

Snags marked and recorded on paper

Opportunity to improve traceability with digital records

AIRBUS





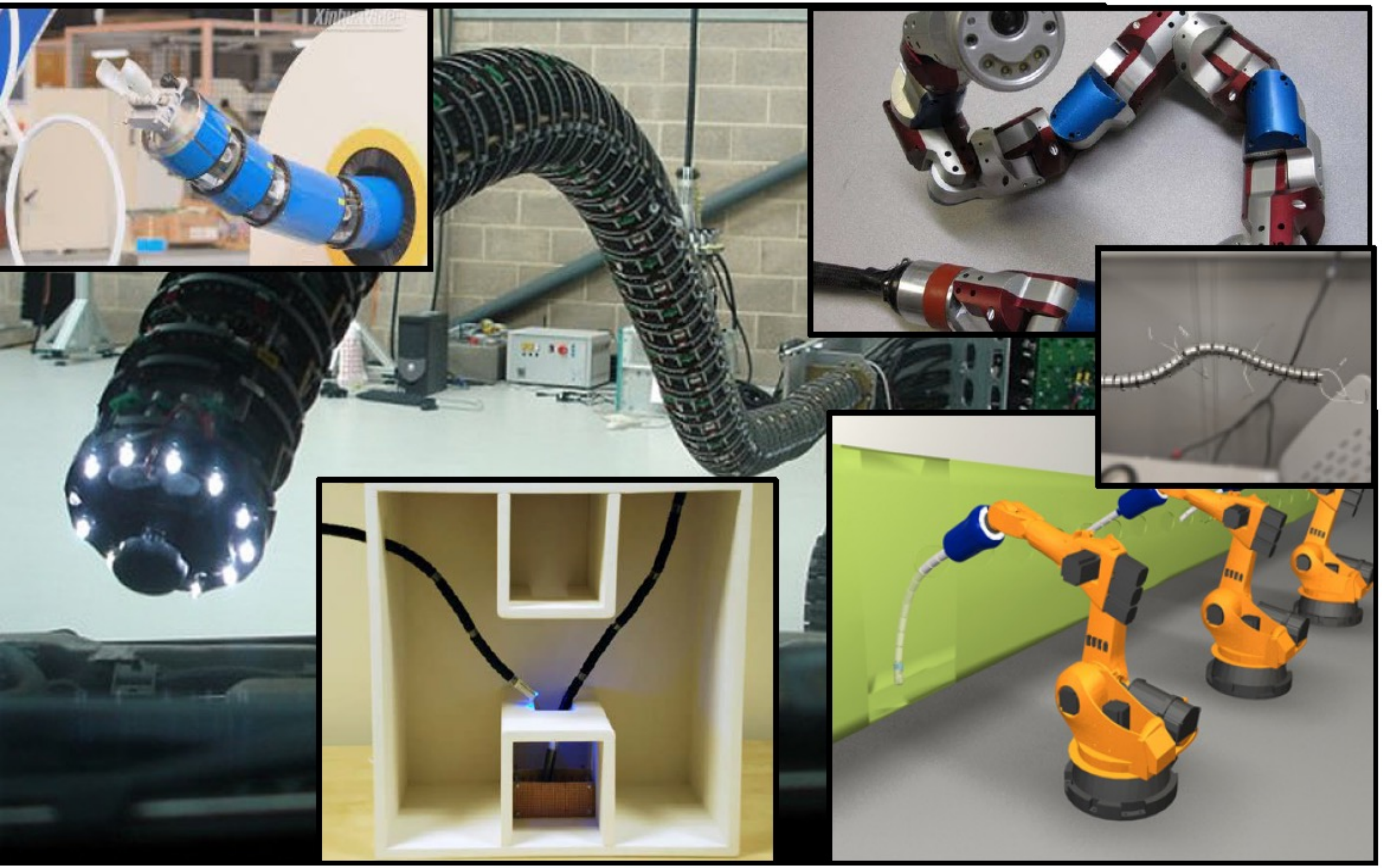
<u>Challenge</u>:

In service access to wet tanks

Beyond inspection during wing assembly the presence of fuel / fumes in the FAL and in service presents additional demands and risks

Solution needed that's suitable for cost effective deployment across range of airlines and locations

AIRBUS



Solution?

Robotic Manipulator Arms

Use of snake arm or other robots to secure access to confined spaces

Need to be able to safely access a range of spaces, carry an end effector load, avoid collisions, track location, recover from failure etc

AIRBUS

Solution?

Deep Learning for Anomaly Detection

With a source of in tank images AI /DL techniques could be used to automatically identify areas for closer inspection

How can we train such models, and be confident that an unpredictable array of snags can be detected?

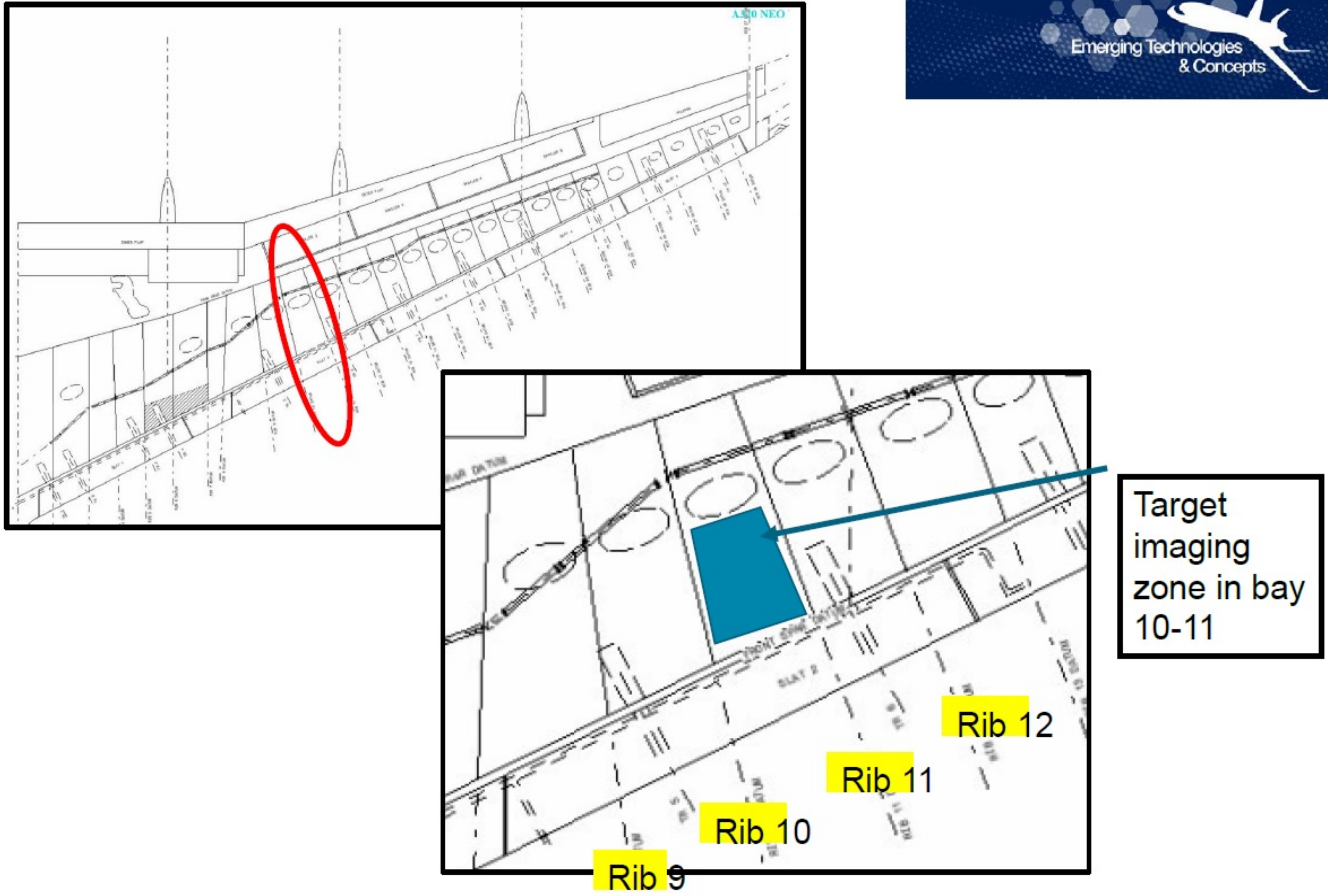
AIRBUS

Main challenges with a Deep Learning approach

- The number of data (images) with anomalies is usually very small (1 every 1M images ?)
- The type/shape of an anomaly can be very different (basically any shape different from a clean bay)
- Lack of data (clean and with anomalies)

Phase I: the supervised learning approach

- Restrict focus on a specific bay section
- Collect images of clean and anomaly bay (AIRBUS)
- Apply a small Neural Network (lack of data limits the deep of the NN)



Emerging Technologies & Concepts

Airbus CTO:

Proof of Concept (PoC) Incubator

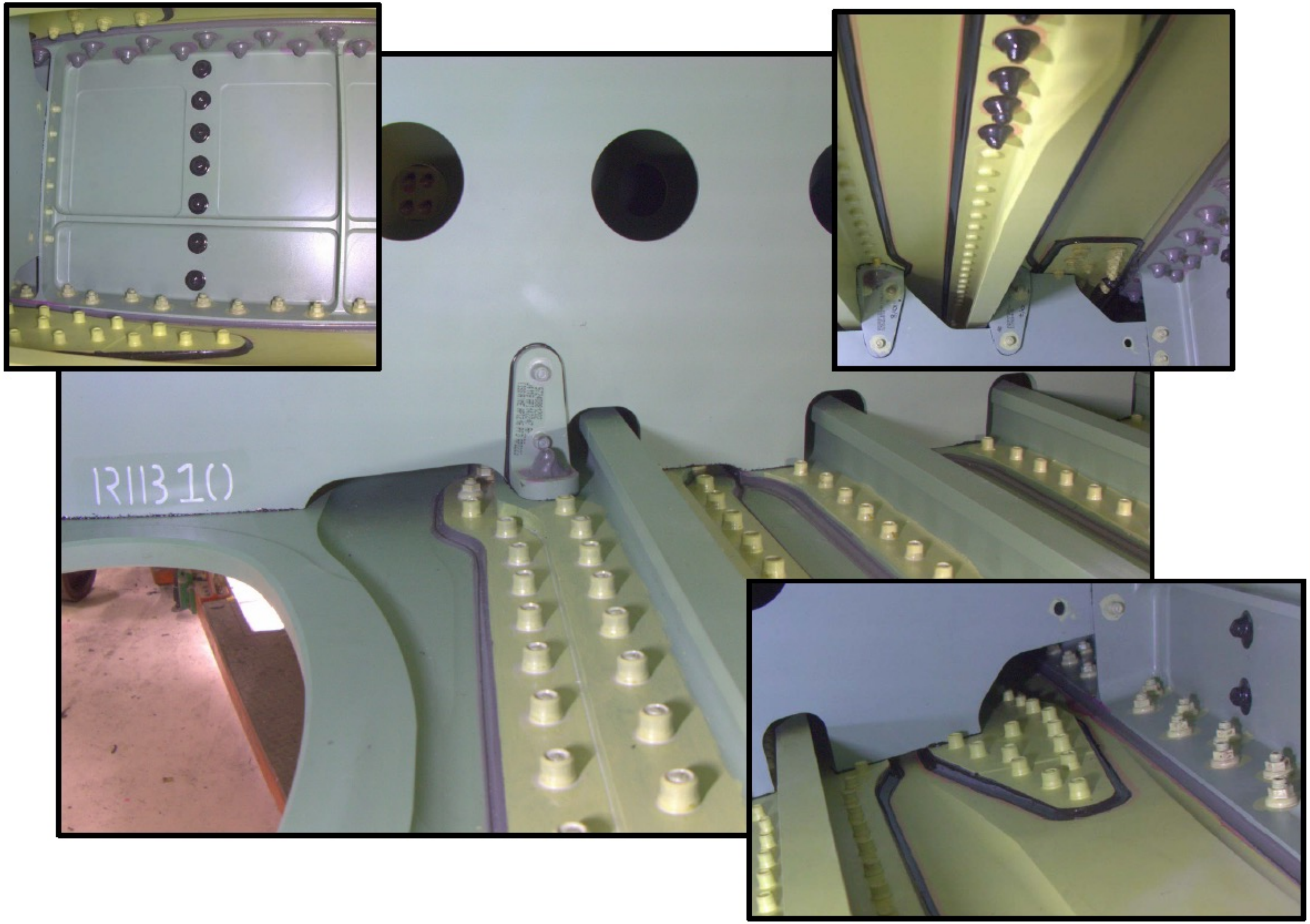
Automated Wing Tank Inspection

- *Remote Visual Inspection*
- *Automated Defect Detection*

Airbus team from CTO, Manufacturing, IM / IT & Engineering

A320 wing Bay 10-11 test case – forward of man hole cover

AIRBUS



PoC Incubator:

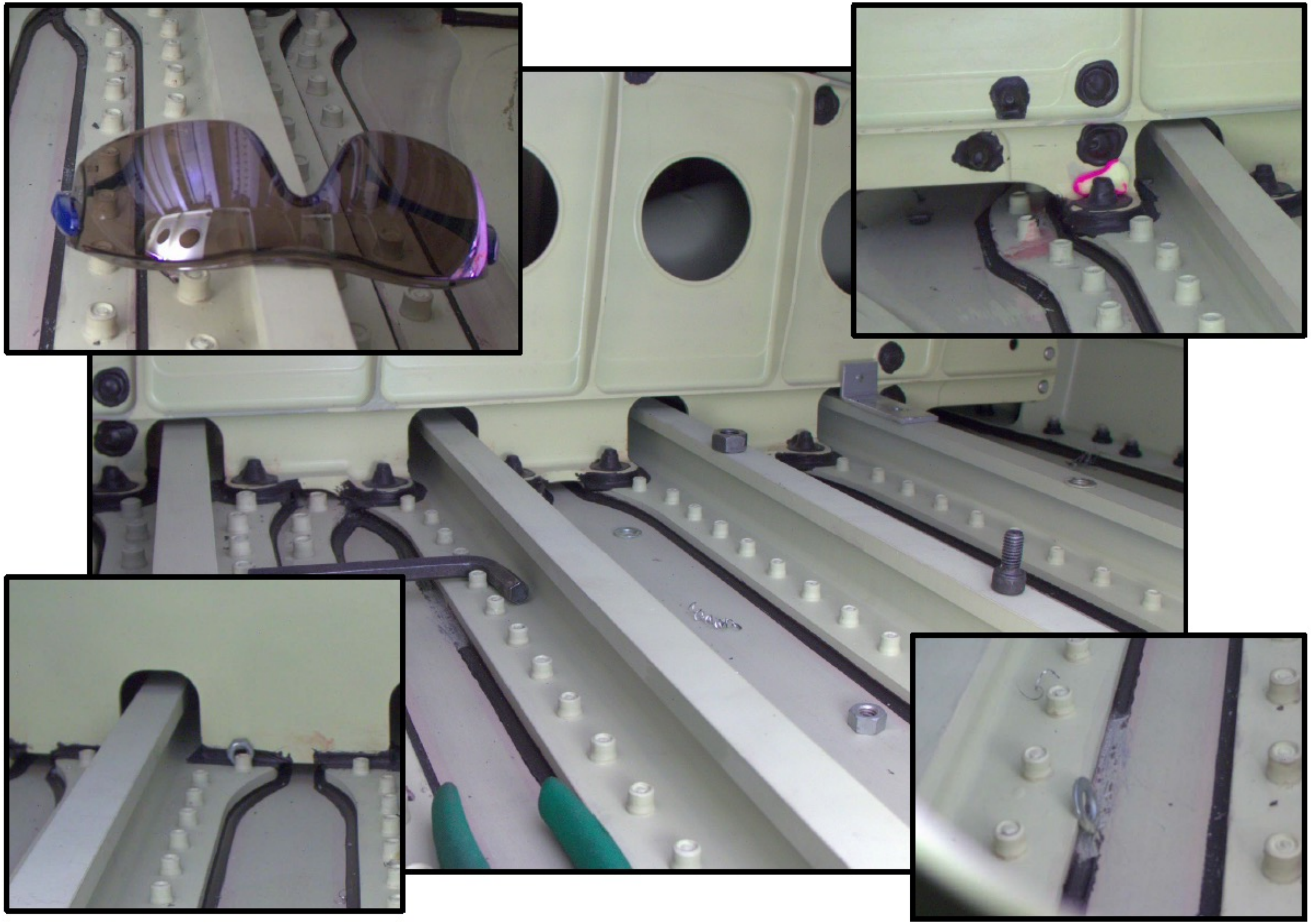
Training image collection on the production line

Single Aisle Stage 1A where no systems or equipment present
- > 40 wings
- 950 images

Included port and starboard wings and different variants:
- A320 / A321
- CEO / NEO

Provides anomaly free image set

AIRBUS



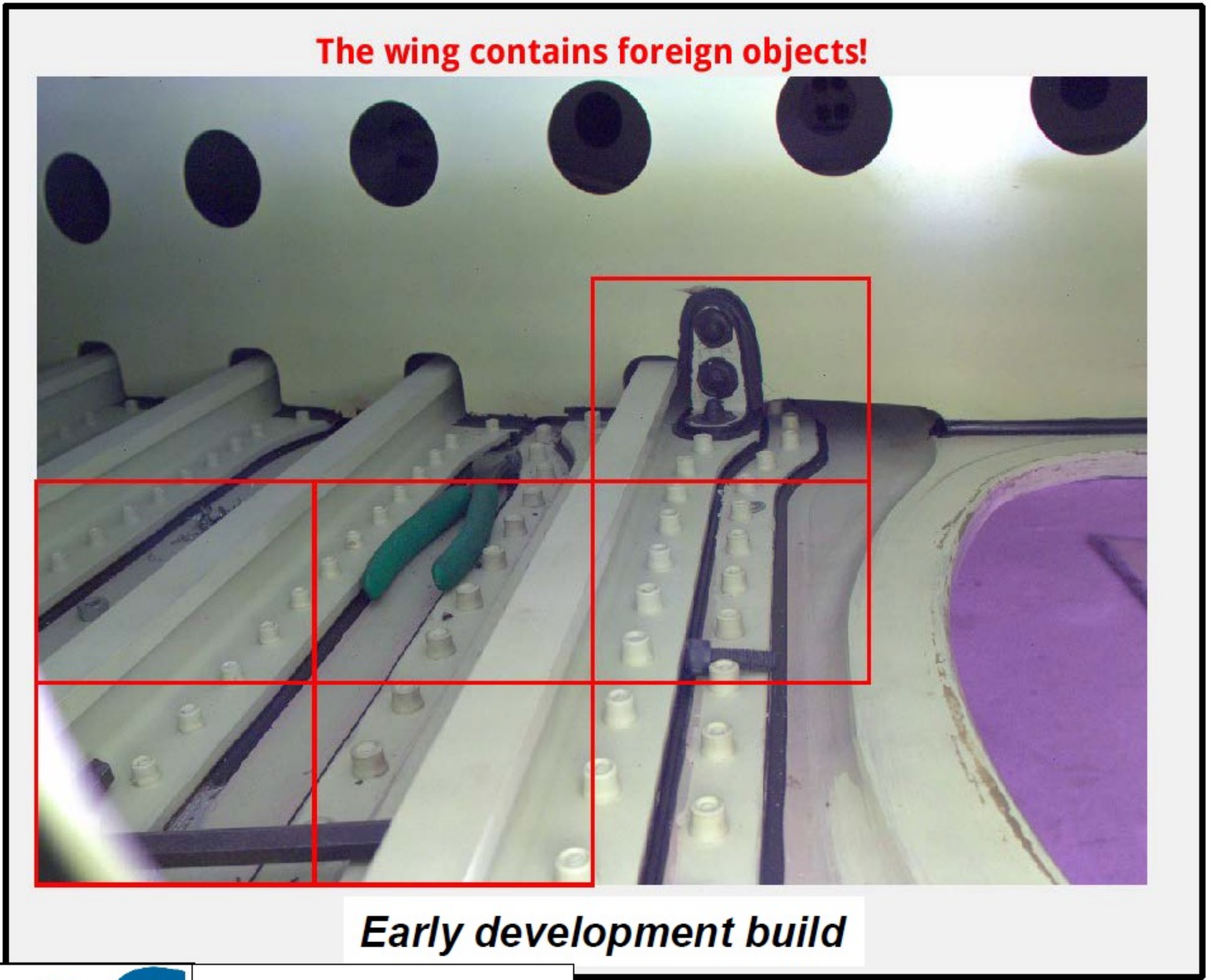
PoC Incubator:

Defect Training images in ProtoSpace

Use of ProtoSpace Wing In Filton to ***stage defect cases***

Generation of >280 images with FO – lower cover:

- *Damaged sealant*
- *Nuts and bolts*
- *Misc Tools*
- *Swarf*
- *Safety glasses*
- *Wire (crack/scratch)*
- *Etc*



PoC Incubator:

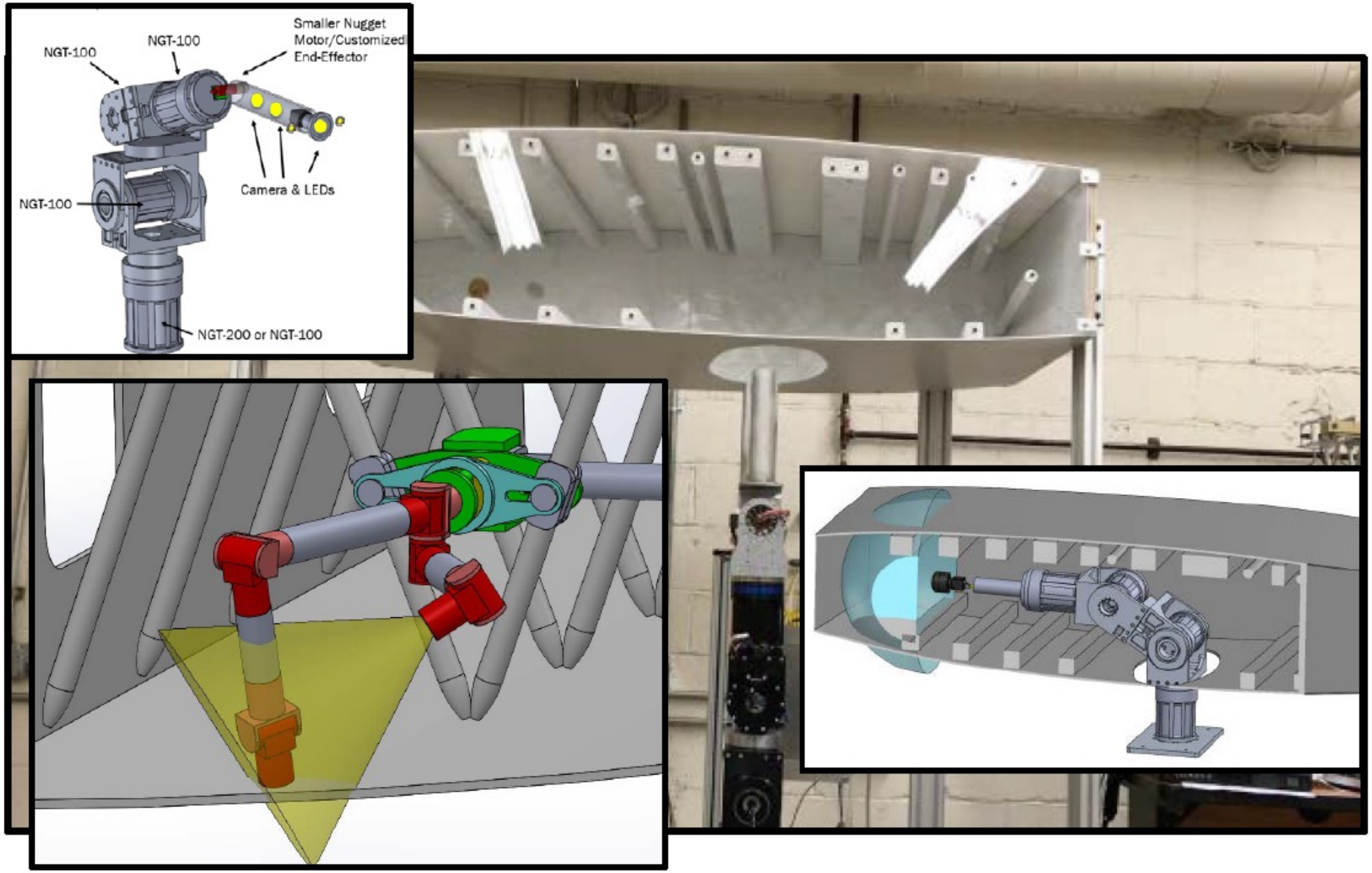
Deep Learning model prototype: ATOS/STFC

Preliminary Training of a Convolutional Neural Network based on Alexnet:

- *Model creation with >1000 images*
- *Train/validate 80/20*
- *Testing set on >50 images*

PoC Incubator:

Modular light weight robot arm with NREC @ Carnegie Mellon



Preliminary modular design concepts under development:

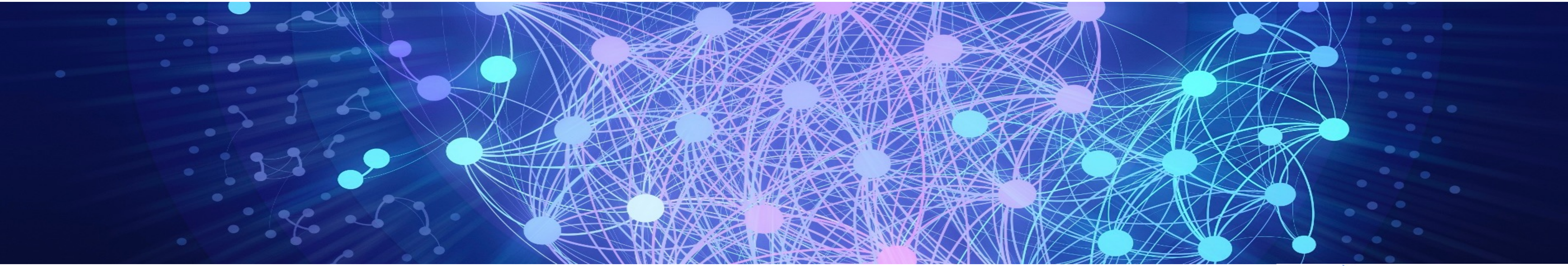
- *Simulation*
- *Configuration*
- *Actuators*
- *Link arms*
- *End effectors*

NREC
EXPERIENCE · EXPERTISE · EXCELLENCE

AIRBUS

Resume from Phase I

- Preliminary results suggest that a Deep Learning approach has a certain potential
- However, it cannot be based on a supervised learning!
- We need a large amount of data!



Phase II: use of a DMU CAD model with semi-supervised learning approach

- Use of Digital Mock Up (DMU) CAD model to generate large amount of data
- AIRBUS has (of course) a well defined CAD model of the wing bay
- However, details (like bolts/sealant/etc.) are missing
- Can we detect defects using a semi-supervised approach?

AIRBUS DMU CAD model

DMU

↓

Produce simple render

↓

Generate video animation

↓

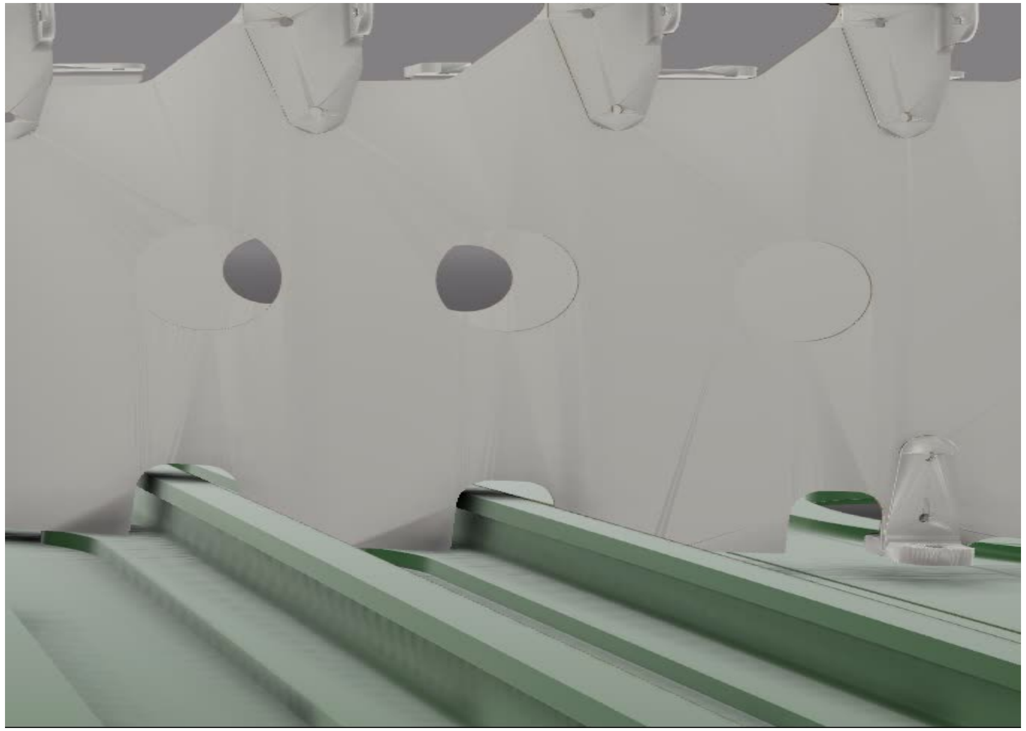
Extract images from video frames

↓

Improve render quality
(Greater photo-realism - Materials, resolution)

↓

Additional details into CAD
(smaller defects e.g. bolts)



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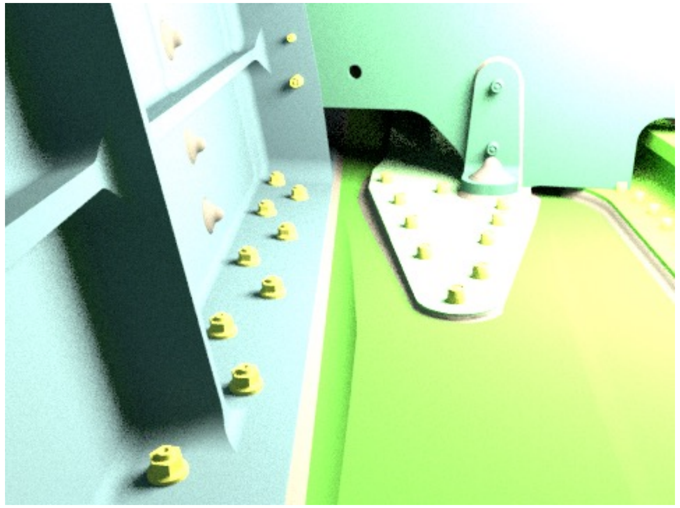
Rendering

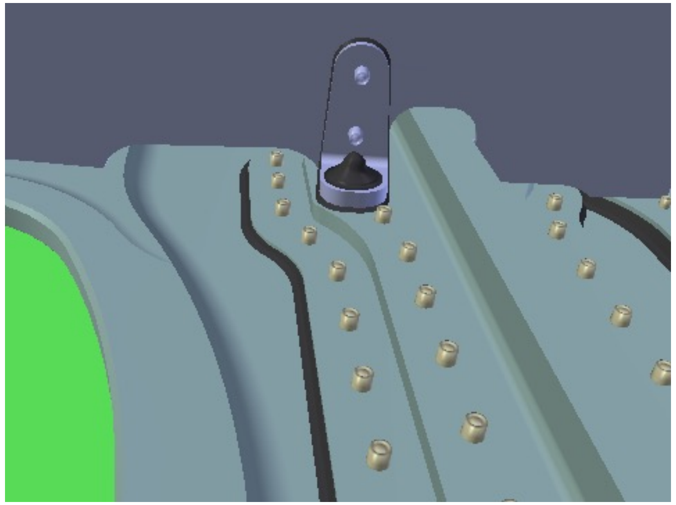
Tested different tools to find good compromise between:

- Costs
- Quality
- Speed

Autodesk Fusion 360
- High quality
- Expensive
- Very slow (10min per image)



Blender
- Medium quality
- Free
- Slow (2-3 min per image)



Blender
- Low quality
- Free
- Fast (3s per image)

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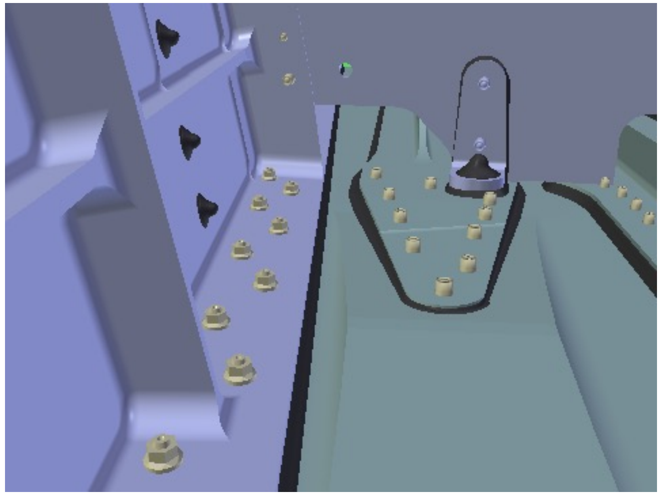
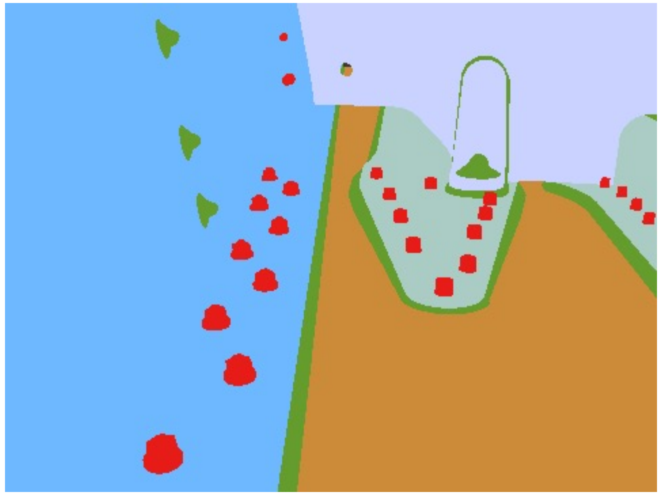
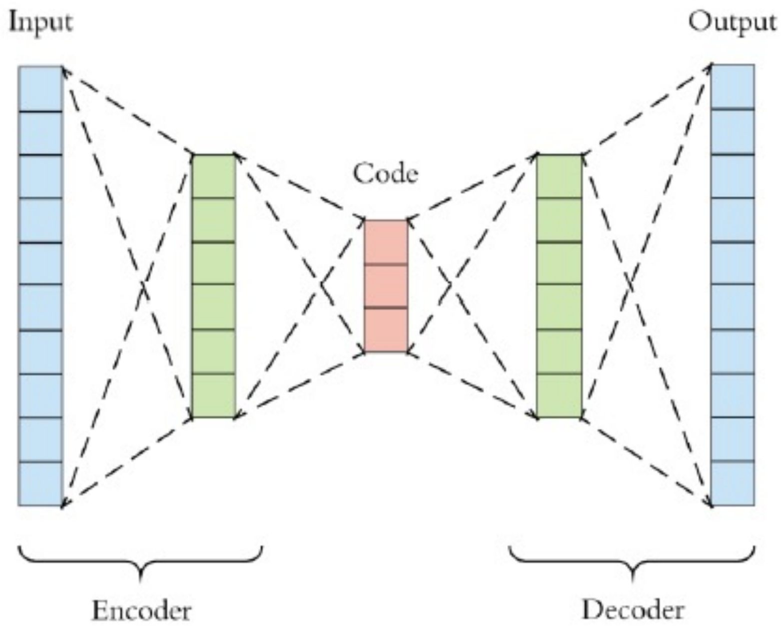
The semi-supervised learning approach



Rendered image

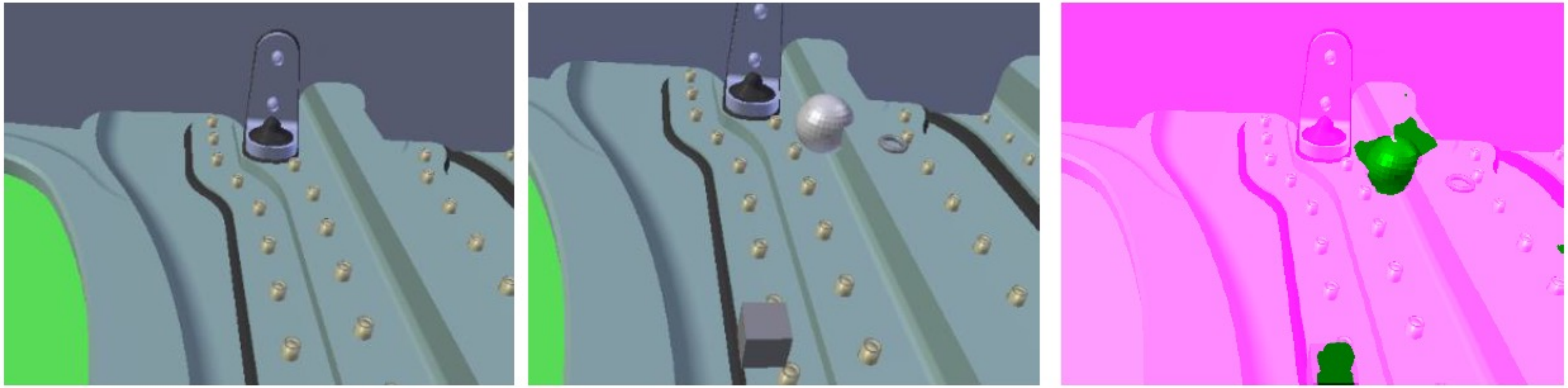


Corresponding mask



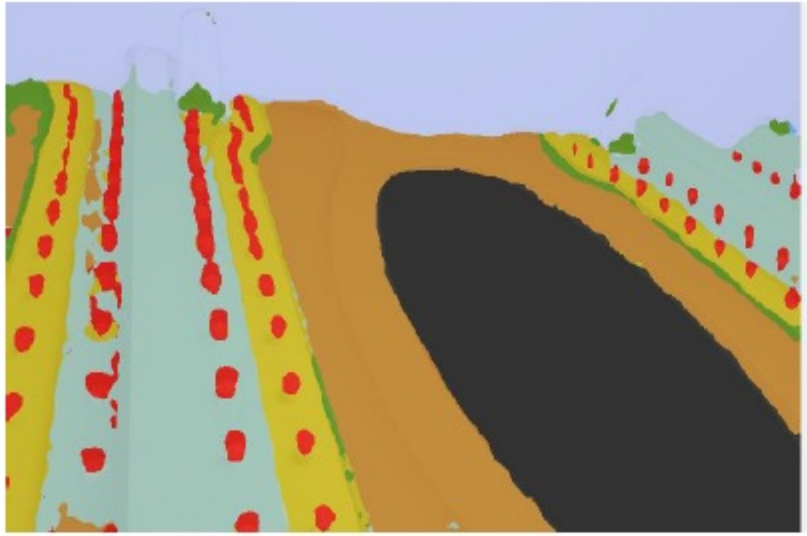
Autoencoder

Inference on Synthetic Defects



a) No anomalies   b) Synthetic anomalies   c) Anomaly detection

Inference on Real Images



Synthetic image

Real image

Very poor results when inferred on the real images!

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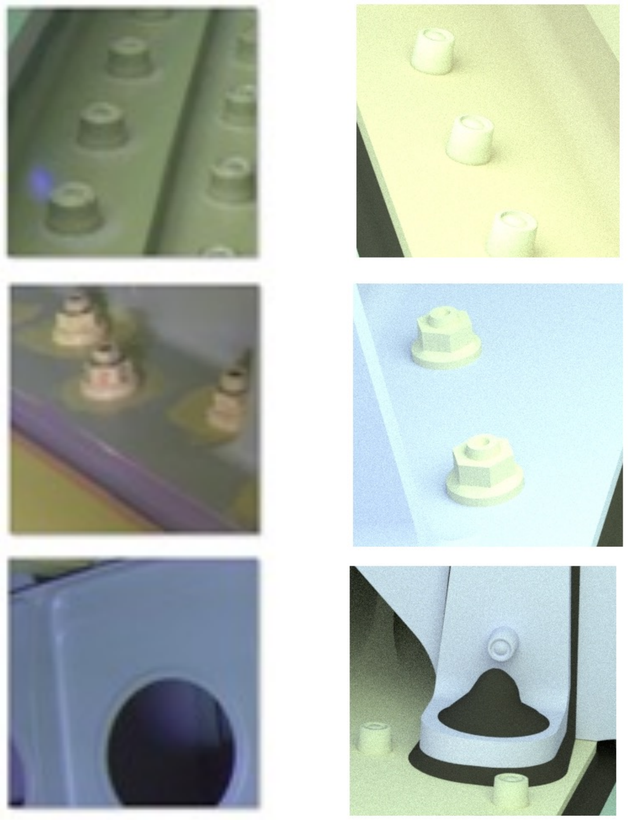
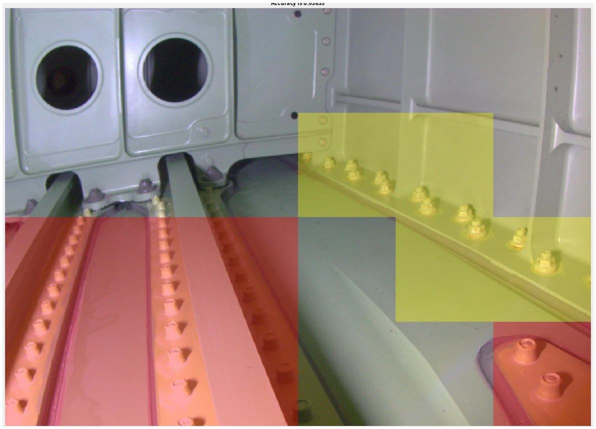
Something in missing…

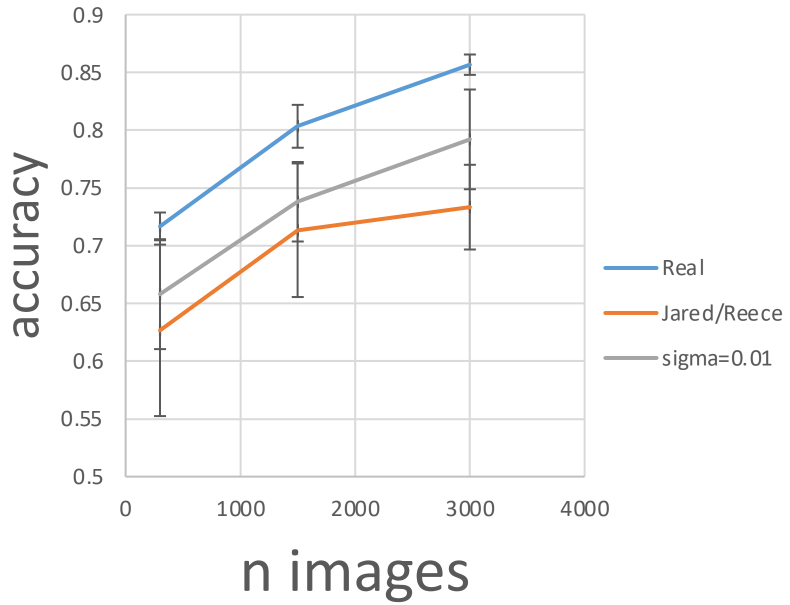
Let’s reduce the problem to a classification of bolts:





Correct results

Best results!



Adding a false background helps!

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Resume Phase II

- The DMU model could be used to generate large amount of data, but need to be augmented with details

- Semi-supervised learning (semantic segmentation) is robust for defect detection

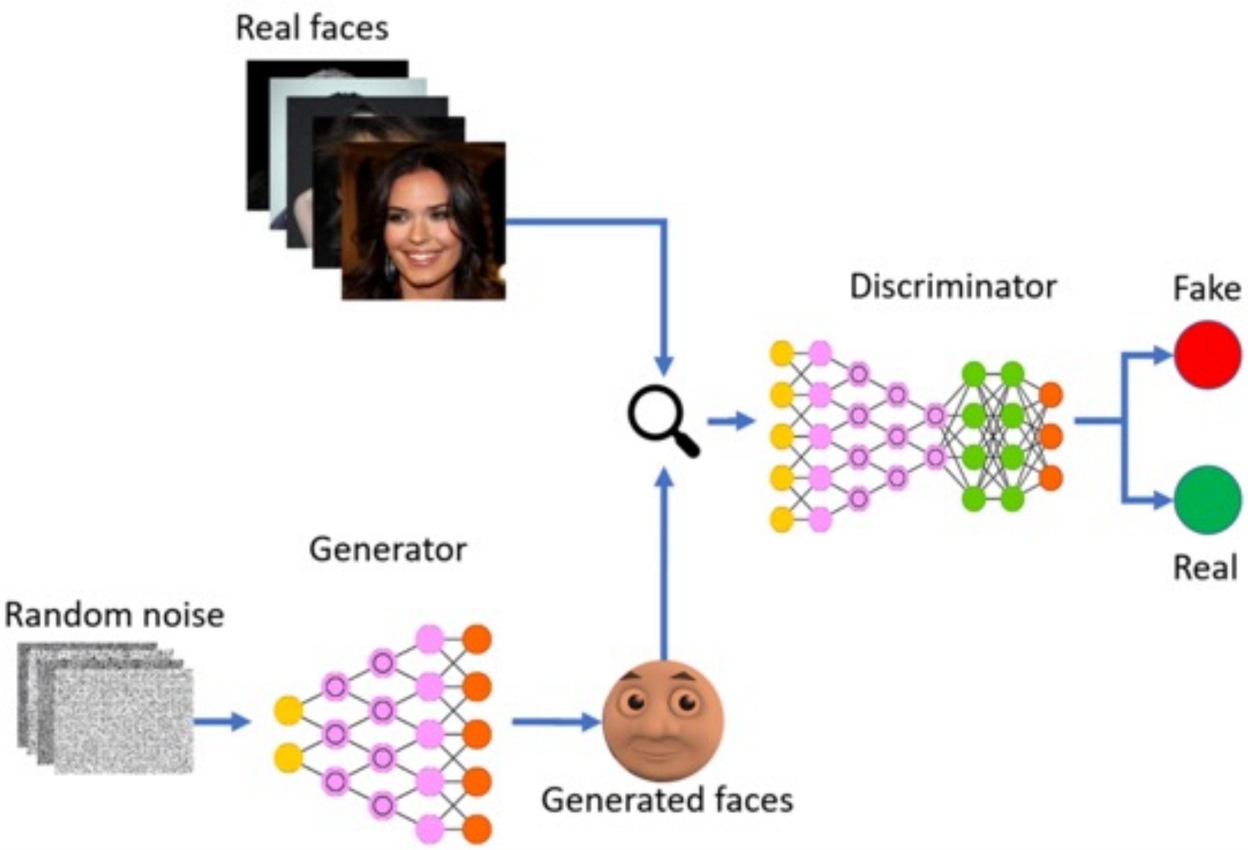
- However, there is a gap between the DMU model and the real images which lead to poor results on real images

- This gap is confirmed also via a simpler classification problem on bolts

Phase III: the unsupervised learning approach

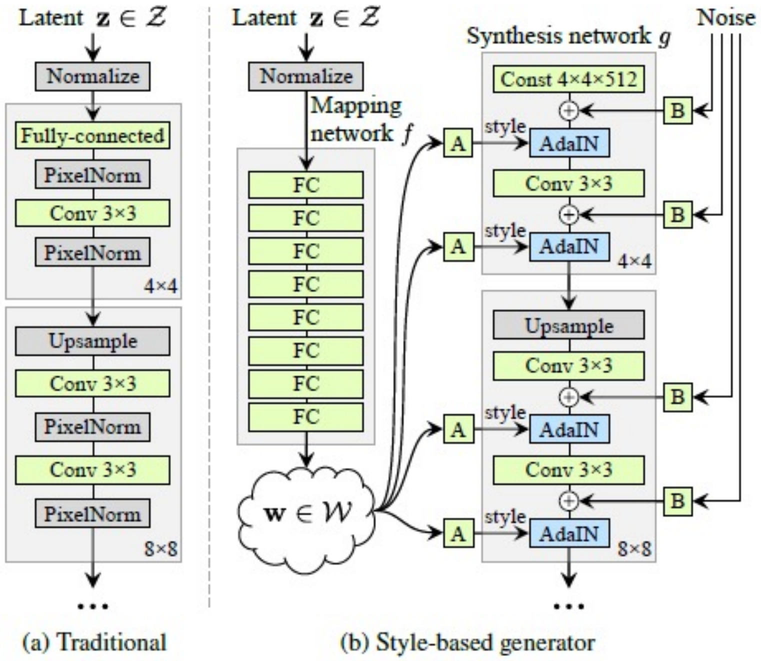
- Can we use Generative Adversarial Networks (GANs) to generate bay images?
- StyleGAN is a leading architecture in high quality generated images
- GANs can be used for anomaly detection (AnoGAN)
- Improved version of AnoGAN via Encoder like in fast-AnoGAN => AStyleGAN

What are GANs?



The generator and discriminator compete each other and eventual achieve a Nash equilibrium

What is StyleGAN?



https://github.com/NVlabs/stylegan

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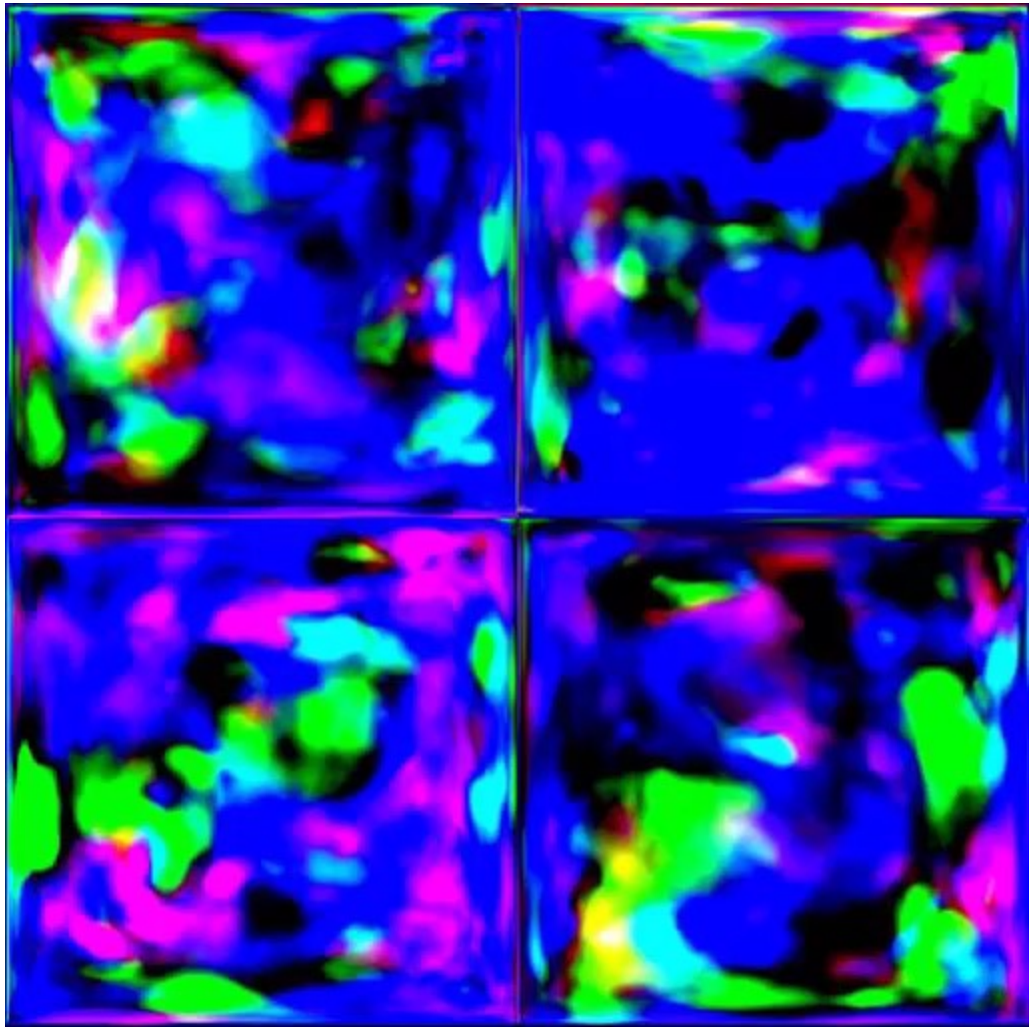
Results of StyleGAN on a wing bay



Actually we use a variation of StyleGAN named MSG-StyleGAN

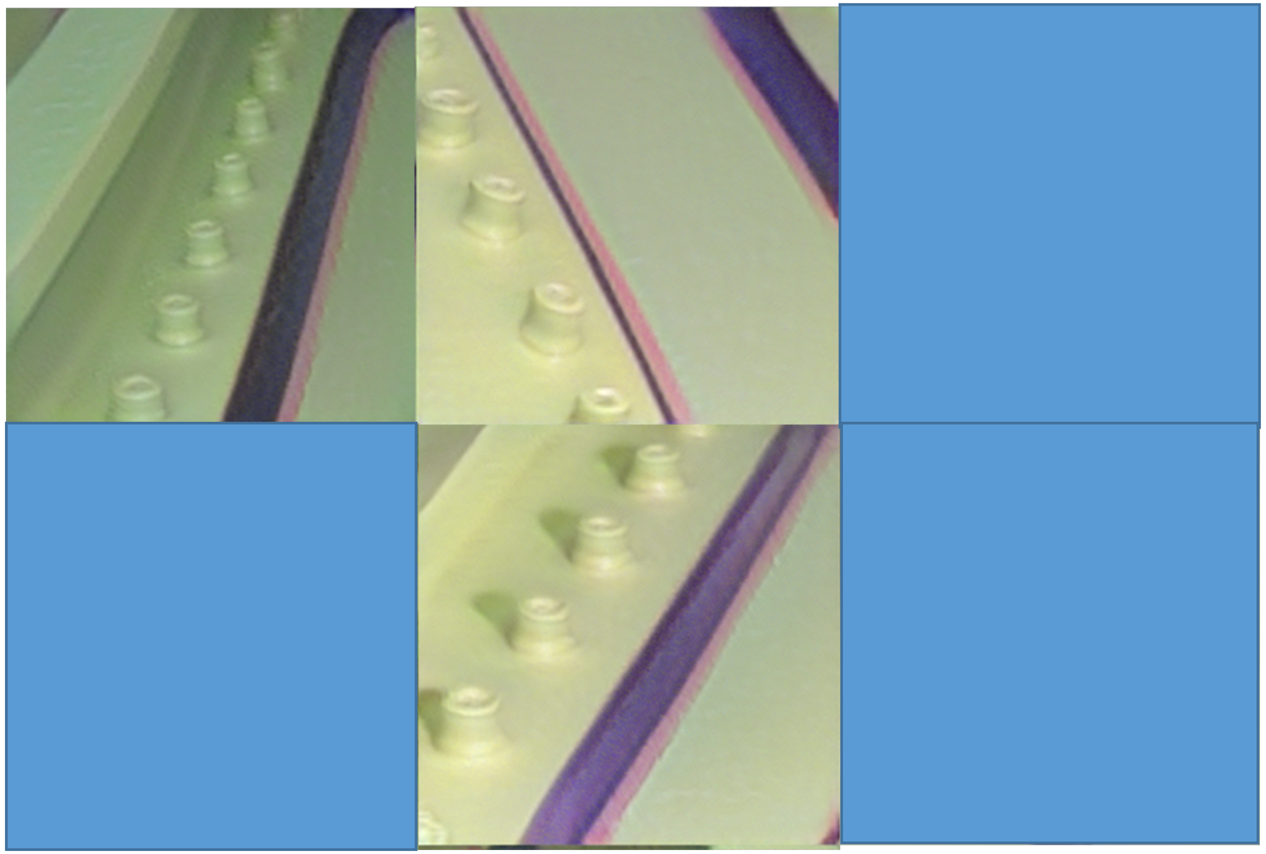
Quality of MSG-StyleGAN

The £1 competition... Which one are fake?

1	2	3
4	5	6

Quality of MSG-StyleGAN

These are fake! But no worry, let's forget the £1…

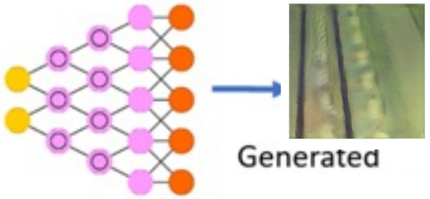


1	2	3
4	5	6

How does AnoGAN works?

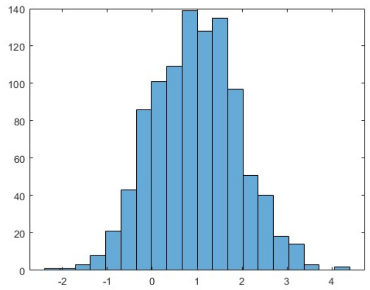
Generator: use to generate the image

Guess random distribution

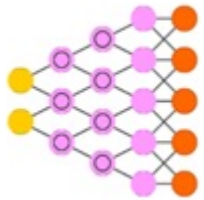


Find pixel differences between the two images

Find feature differences between the two images

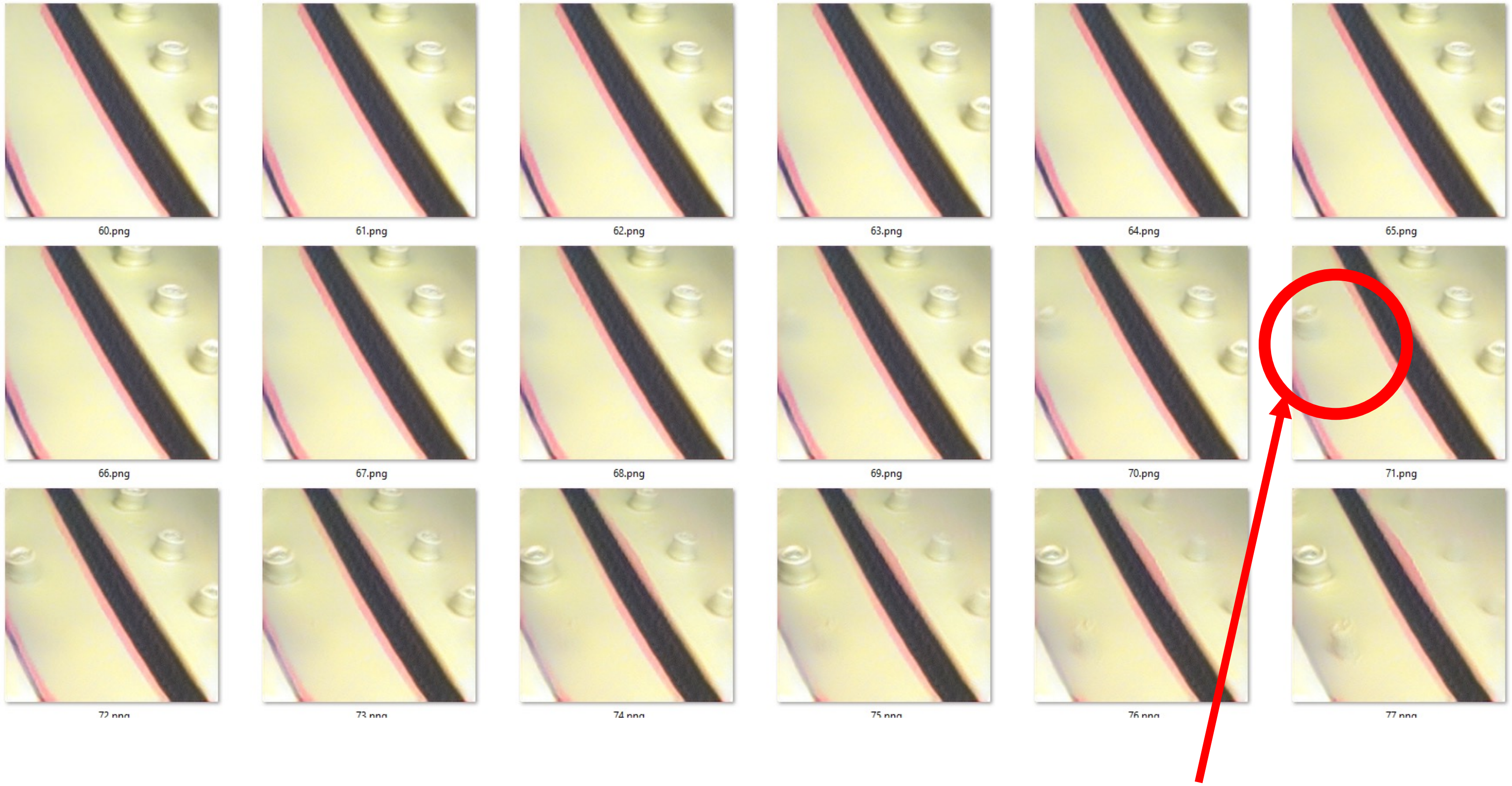


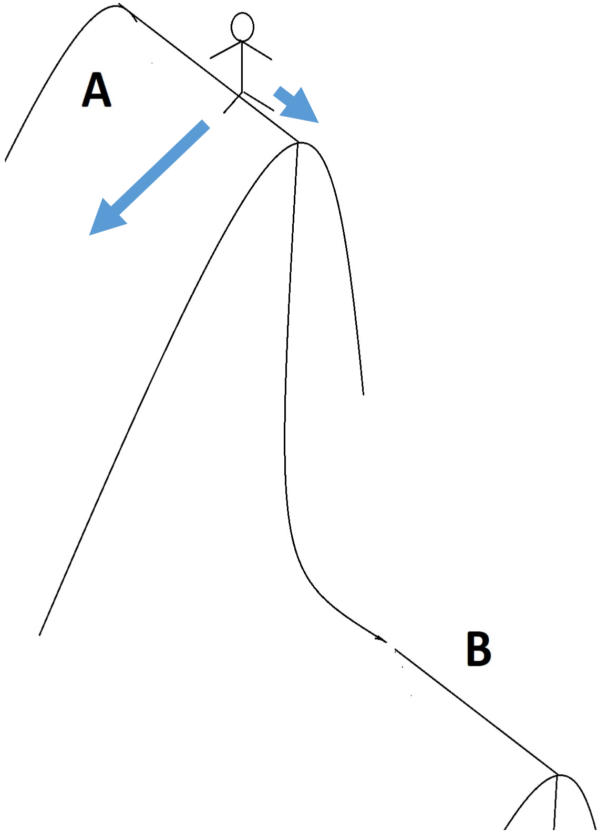
Adjust random number distribution



Generator: use to backpropagate the total differences (weights are frozen!)

Main issue: the morphology





Spurious anomalies
can occur during the
latent research space!

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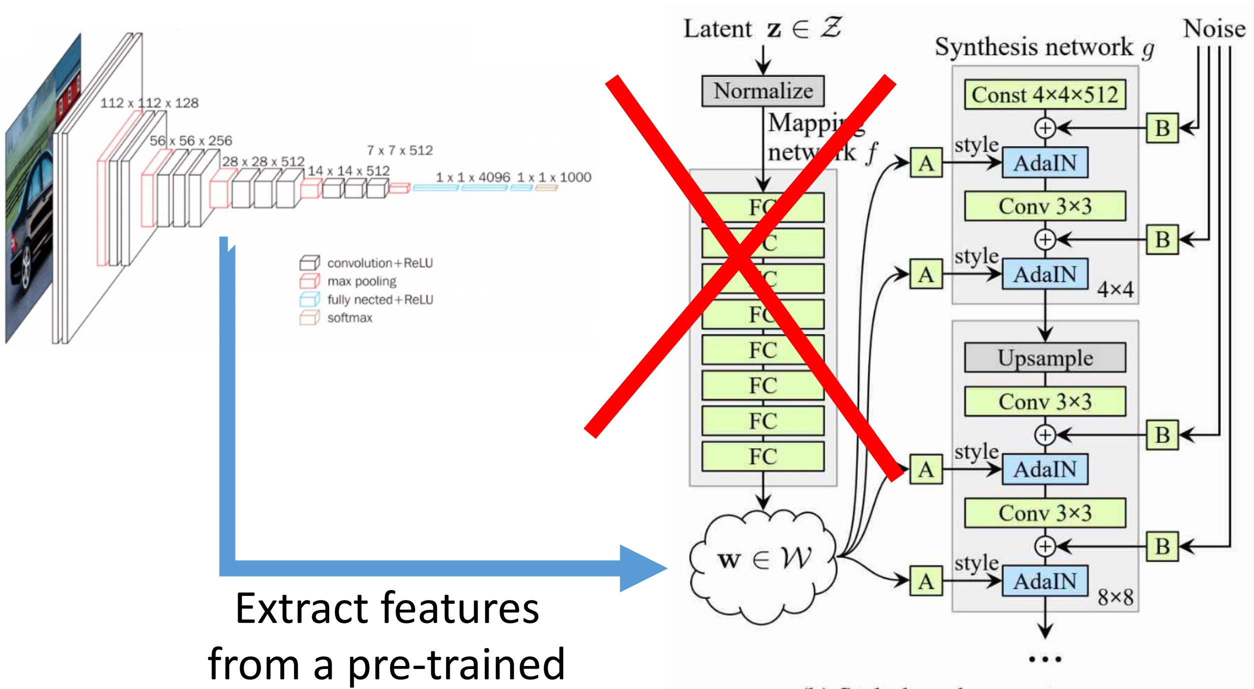
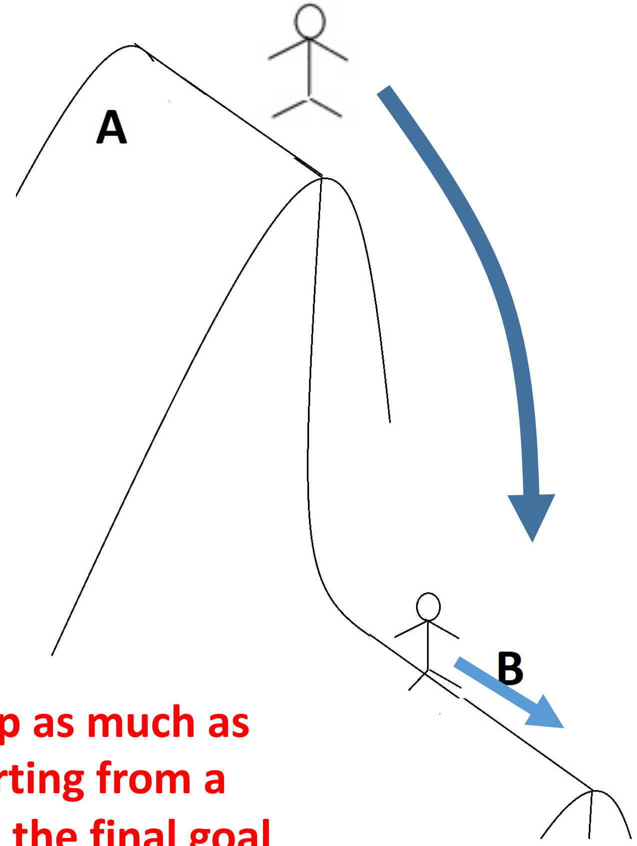
Improvements: add and Encoder like in fast-AnoGAN



(b) Style-based generator

Extract features from a pre-trained VGG network



We try to help as much as possible starting from a closer point to the final goal

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AStyleGAN: Anomaly StyleGAN

real generated differences

Results obtained training the GAN with 375 images (augmented to 10k) only!
Still very small for a usual GAN training…

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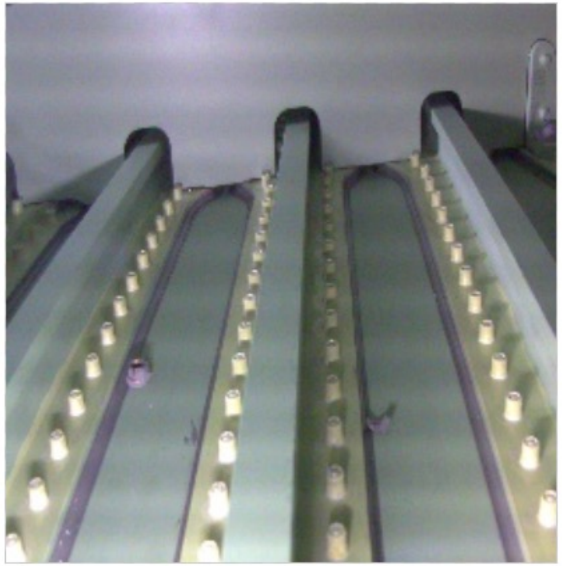
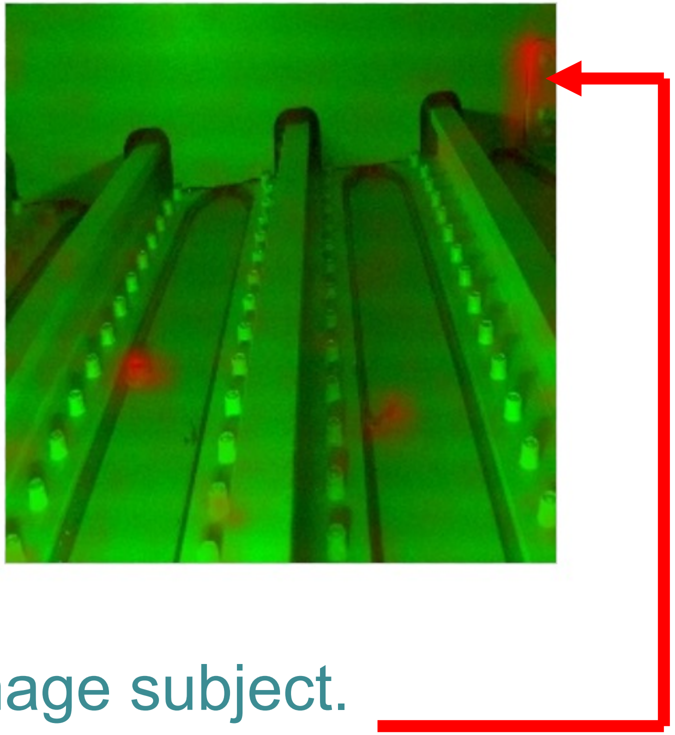
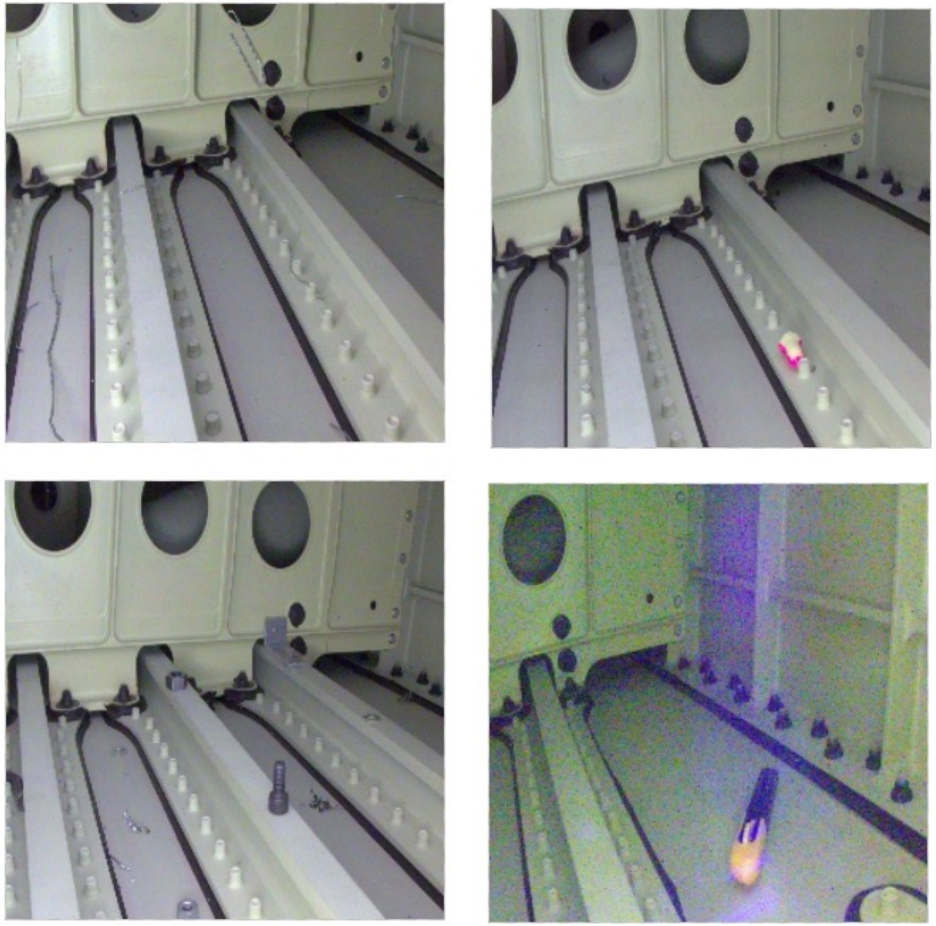
AStyleGAN: Anomaly StyleGAN

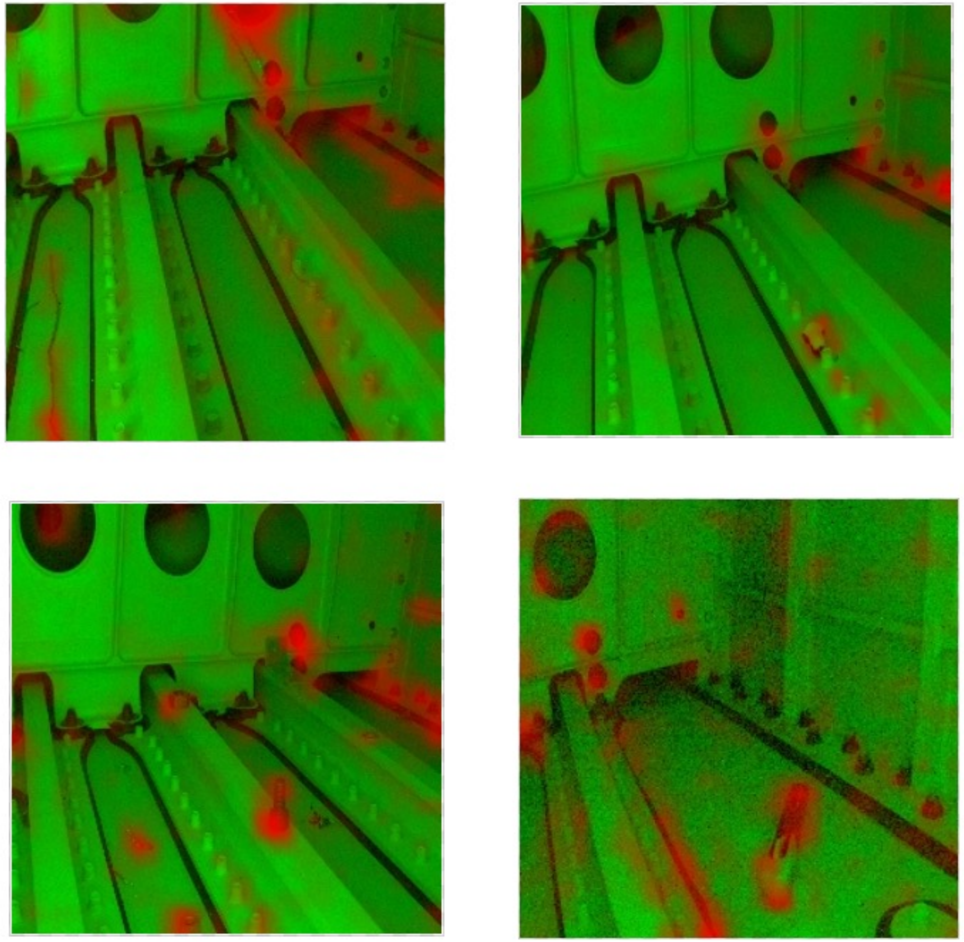




StyleGAN has been mainly developed for a central image subject.
Poor reconstruction on the side ends up in False Positives

Other defects examples

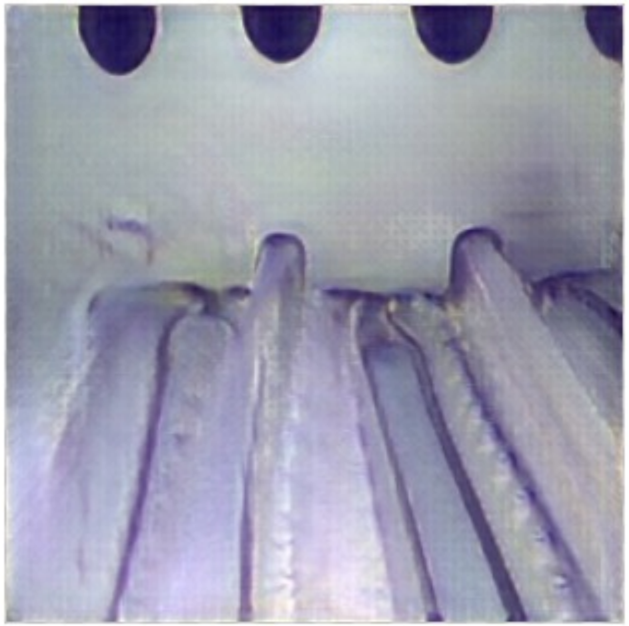




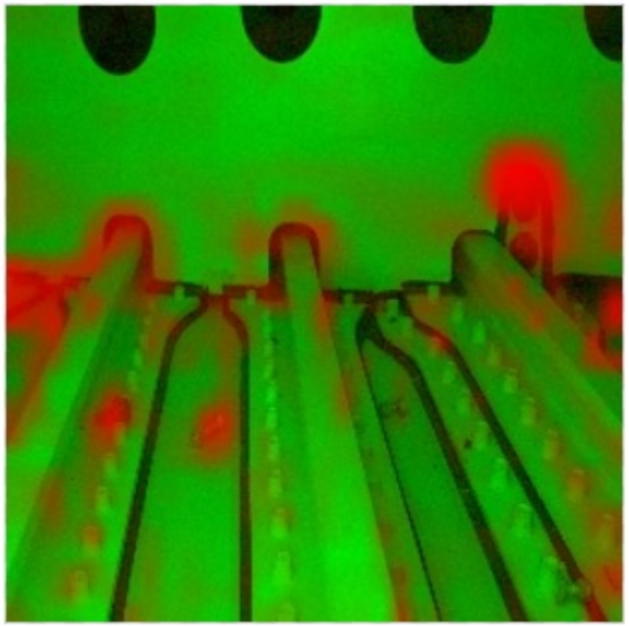
The training dataset does NOT contain any of this images and only a very small proportion of clean Protospace images

Distortions due to local minima

Real image



Generated image



Differences

The encoder may start from a very wrong location!

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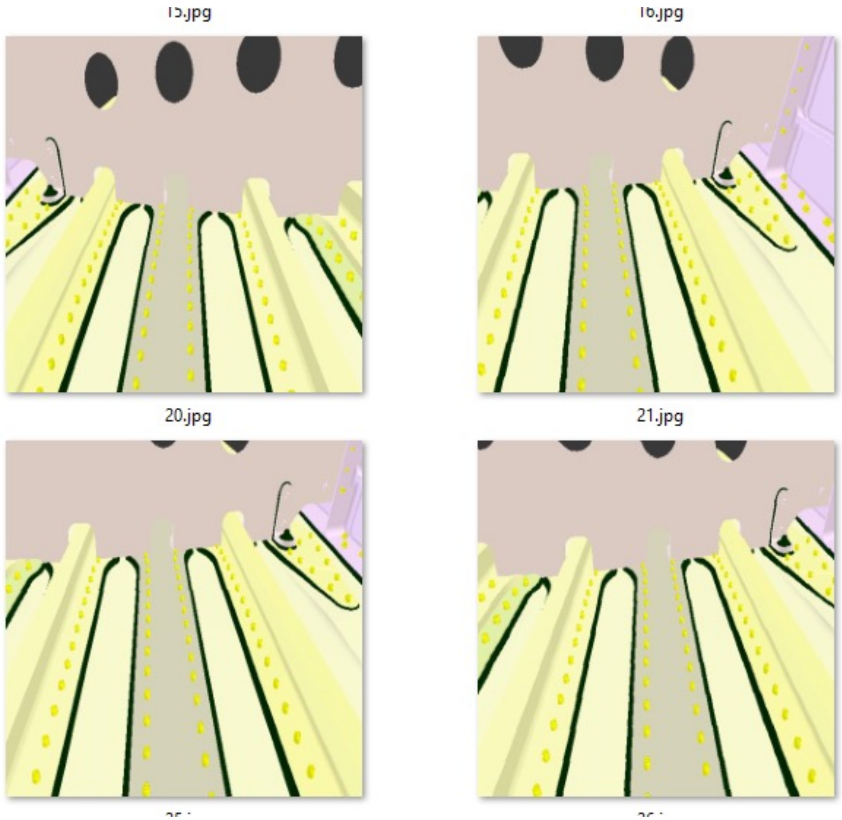
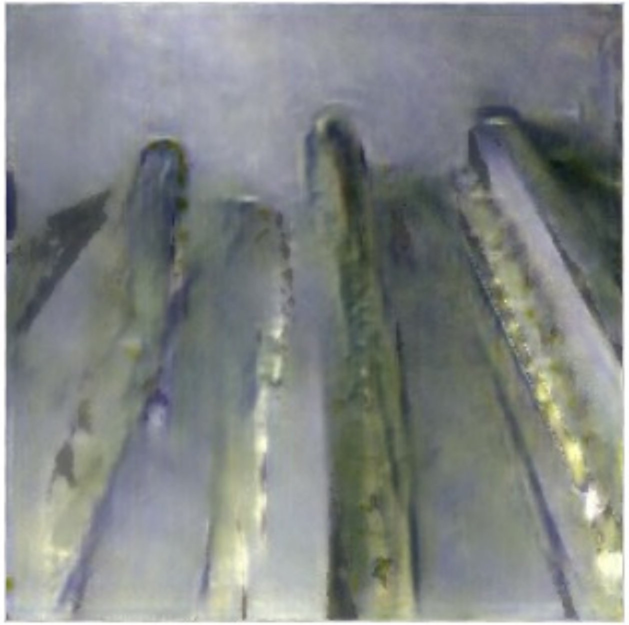
Training with synthetic images



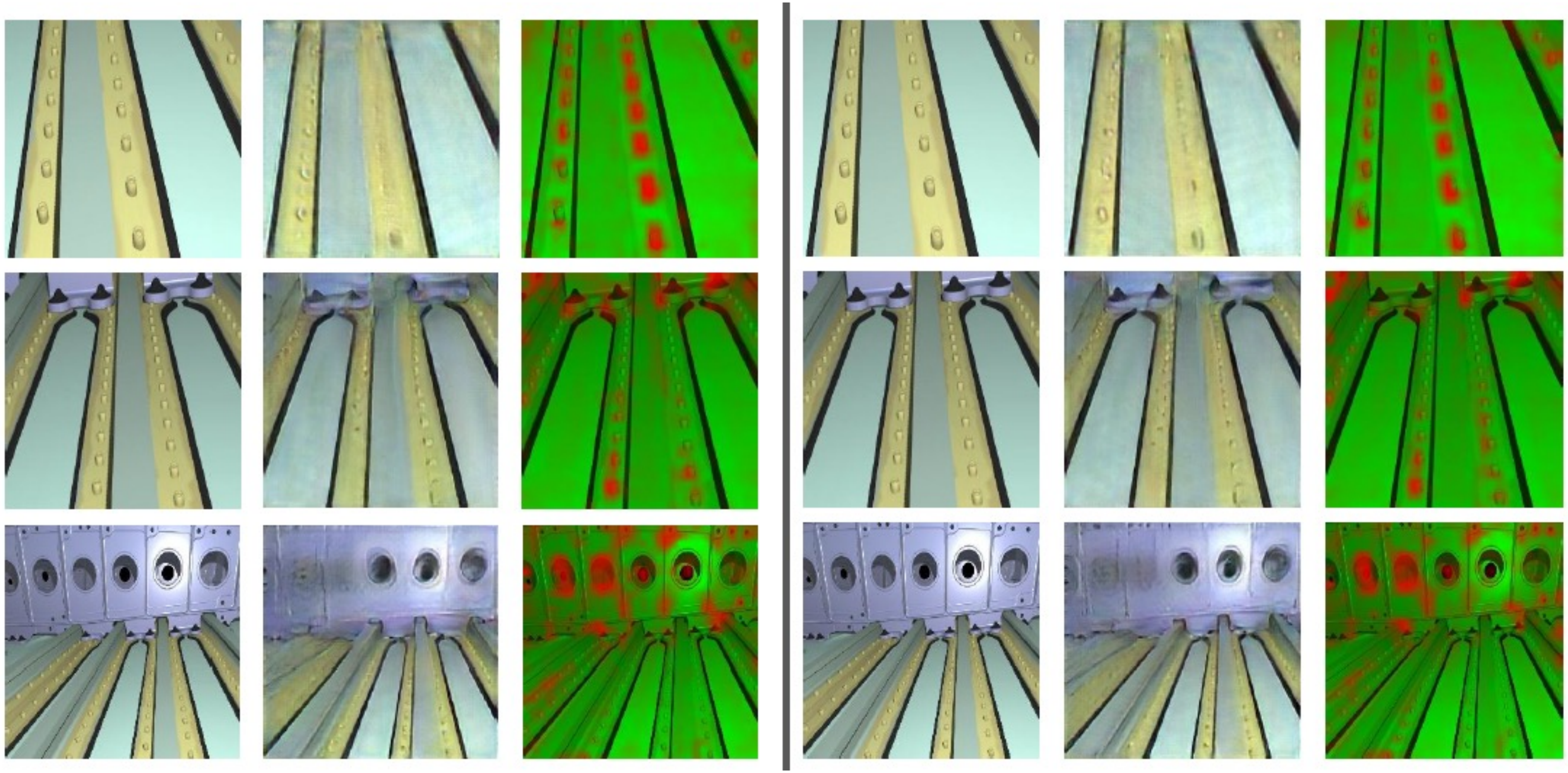
Real



Generated

10k synthetic images obtained via Blender using different colours

Inference on synthetic images (from Pablo Bermell)



It could be used as augmenter of the synthetic DMU model

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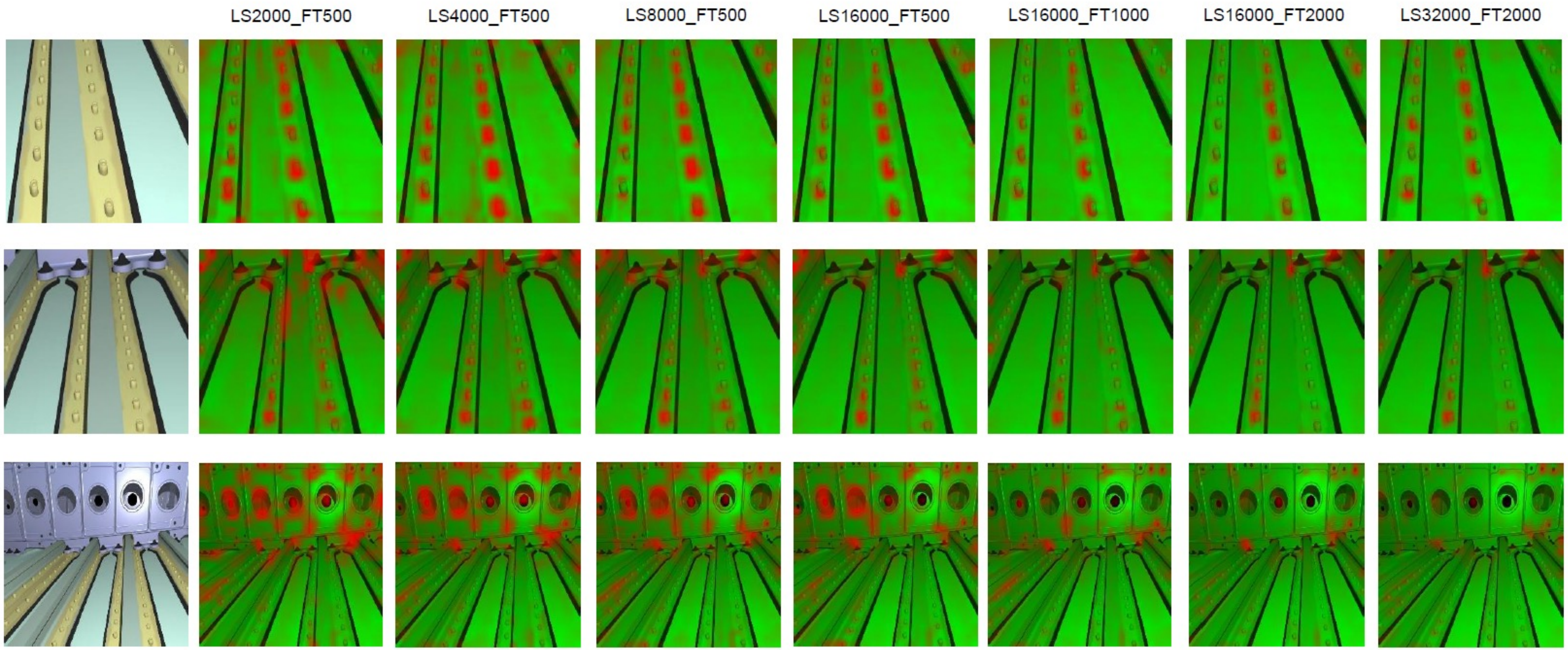
Inference on synthetic images (from Pablo Bermell)

False positives - impact of iterations, (LS: latent space, FT: fine tuning)



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Resume Phase III

- Unsupervised learning can tackle the anomaly detection based on clean bay images **only**
- It is **agnostic** to the defect and does not suffer of class imbalance data
- Generative NN are promising in their capability of reproducing real images
- AStyleGAN shows good preliminary results but still far for industrial applications

Conclusion and Future Work (I)

- We explored different methodology to tackle the challenging anomaly detection in a AIRBUS A320 Wing Bay 10-11 scenario

- The challenge is that anomalies are rare and can be of any shape

- Generative NN are promising in their capability of reproducing real images

- AStyleGAN is agnostic to the defect and does not need images with anomalies. Preliminary results are good but still far for industrial applications

- AStyleGAN is easily transferable to other bay/sections. You “just” need a lot of data!

Conclusion and Future Work (II)

- To train using a larger dataset
- Improve the Encoder to have a better reconstruction and avoid False Positives and reduce the detection speed (currently ~2 min)
- To remove the fine tuning of AStyleGAN which could lead to False Negatives!

Any questions?