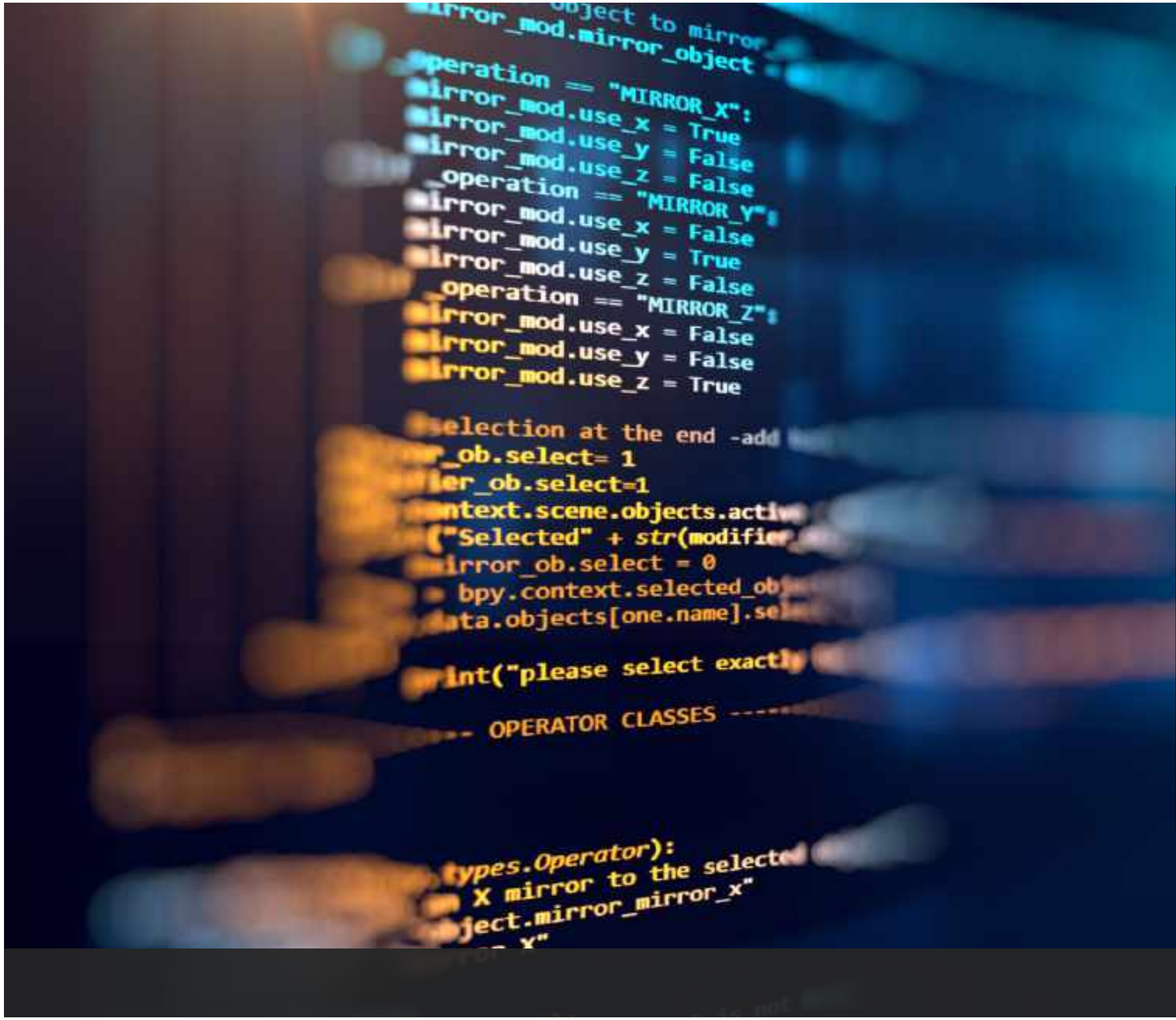


UAVs in the Inspection of Aircraft

N P AVDELIDIS

InnoTecUK

Company History

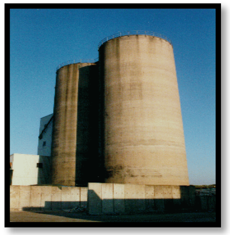
InnoTecUK was incorporated in 2009,and grew to have 42 employees and a turnover of £3.4 million in 2018.


Power Lines


Petrochemical


Buildings & Structures


Oil Tanks


Power Stations

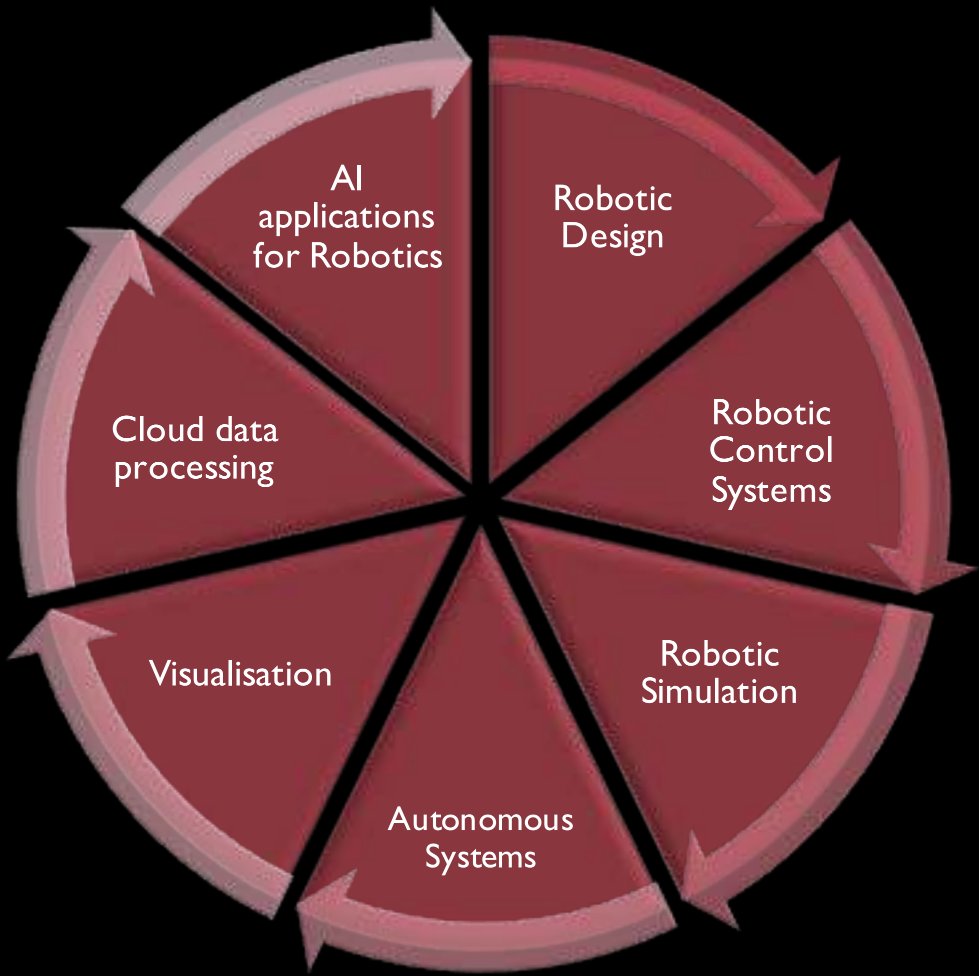

Ship Hulls

Progressive company with extensive networks and expertise in Robotics and Automation for Non-Destructive Testing (NDT).

Focused on developing new technology for Asset and Structural Integrity monitoring and inspection.

FS 693090

Our Technical Expertise



WHAT IS A DRONE?

- Unmanned Aerial Vehicle (UAV) known as drone is **a type of aircraft** that operate without humans onboard.

- Autonomous systems must be able to **make decisions** and **react to events** without direct interventions by humans.
- The **aerial NDT inspections** provides a wide range of possibilities which take the advantage of the **movement exibility and mobility** of the drone plus the non-destructive nature of the conducted tests.
- The drone-based inspections supply **safer** and **faster** solution to fulfil the requirements and prevent unexpected shutdowns.
- Drones let experts to perform inspection and maintenance **more regularly** throughout its **service life**.

Unmanned Aerial Vehicle (UAV)
Unmanned Aerial System (UAS)
Drone
Remotely Pilot Vehicle (RPV)

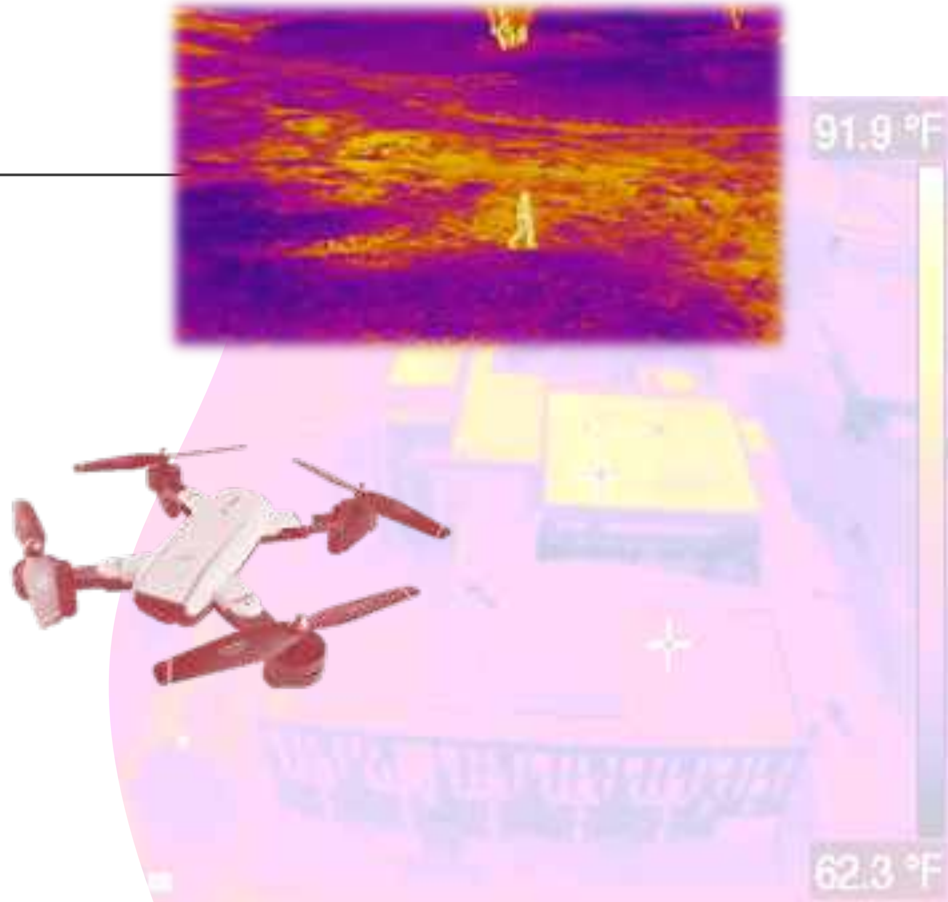
INSPECTION USING DRONES

- **Non-destructive testing** (NDT) is the process of inspecting specimens, components, or assemblies for differences in characteristics or any **discontinuities** without destroying serviceability of the specimen.

- Non-destructive tests are employed to:
  - Ensure **product integrity** and **reliability**
  - Lower **production costs**
  - Maintain a **uniform quality level**.

- Aerial Visual and Thermographic Inspection:
  - Reduce **operational costs**
  - Minimize **safety risks**
  - Increase **accuracy** and **reliability**.

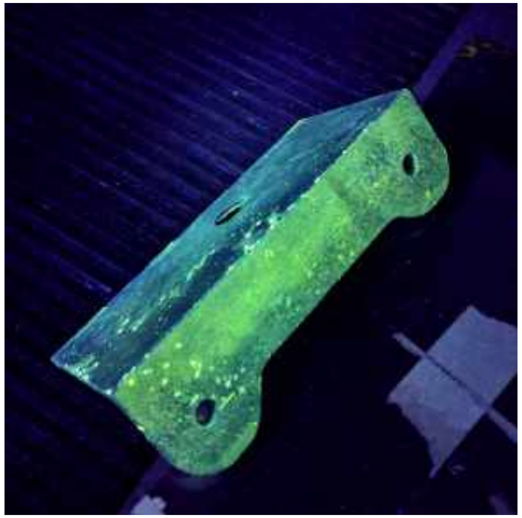
- Drones can **safely**, **economically**, and **efficiently** carry out a broad variety of inspecting and surveying services .



PENETRANT LIQUID INSPECTION

It is usually a six-stage process:

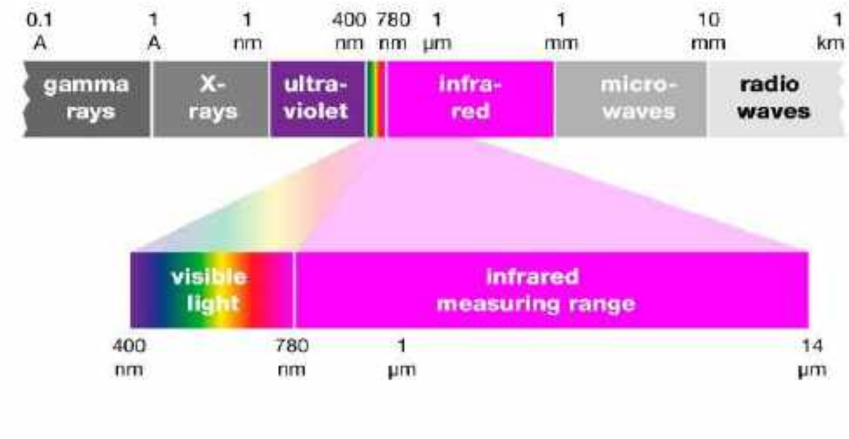
- Surface cleaning
- Application of a fluorescent penetrant liquid (dipping, spray, brush)
- Removal of excess penetrant (solvent, water)
- Application of developer
- Inspection of test surface under UV light
- Post-inspection cleaning (anti-corrosion solutions)



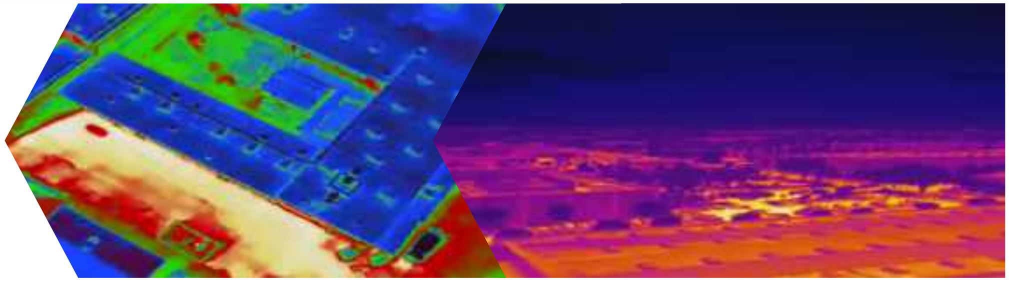
Metallic part with fluorescent penetrant liquid under UV light

INFRARED THERMOGRAPHY

- IR thermal vision is the capability to detect and measure by artificial means, the IR radiation that all bodies with temperature above 0 K emit.



- IR vision is aided by computer sciences to process the acquired information.



CHALLENGES OF INSPECTION

CHALLENGES	DRONE SOLUTIONS
Remote or **hard-to-access** areas	Provide **mobility** and allow inspection regardless of its **design** and **location**
Inspection of specimens with high **structural complexity**	Drone's **flexibility of maneuver** let comprehensive, **reliable** and **accurate** data collection and inspection from **different aspect**
Repetitive equipment **setup** and initial **calibration** facing large specimen	Drone's **fixed setup** reduce inspection **time** & **cost** and lead **regular inspection** and more **accurate** results
Hands-on inspections can cause **damage** and human **injuries**	Due to **autonomousity** of the drones: (a)Reduce **number of personnel** and inspection. (b)Reduce the future **incidents**. (c) Executing **preventive measures**
Inspection **costs** and **time** is one of the key factors which can force industries to less **regulated commitment**	Autonomous flights can reduce **cost** of **human resources**, **accommodation**, **equipment transfer**

CHALLENGES OF AERIAL INSPECTION - I

- Aerial thermographic inspection including: (1) **Data collection** remotely (2) **Real-time** or **Post-process analysis**.
- Remote inspection approach **cannot benefit from hands-on** survey by inspectors at least during the mission. Therefore, providing **extensive information** about the specimen and the environment is essential in many cases.

Differentiate: **surface deformation** and **actual defects**	Surface deformations such as **corrosions** or **stains** can cause abnormality in thermal images which can led to **misdetection**.
Effect of **Reflection**	Structures with high **reflectivity surface** can cause **misdetection** and **distortion** in thermal images.
Drone's effect on the inspection	The **effect** of drone's components like **rotors** on the involved objects in **active thermographic** inspections.
Lack of enough **information** for further analysis	Thermal images do not provide enough information on (a) **surface structure**, (b) the **location** of **defects**, (c) extended peripheral **semantic information** of the neighboring area.
Size of **collected** data	Transmission of **multi-spatial data** can be a challenging issue due to transmission limitations.
Power supply	**Aerial inspection** using multiple sensors requires a large **power source**

CHALLENGES OF AERIAL INSPECTION - II

Collision Avoidance	• **Protection** structures • **Proximity** sensors • **Laser** Range finders
Indoor Localization	• Installed **auxiliary** equipment • **Self-positioning**
Effect of Reflection	Structures with high **reflectivity surface** can cause **misdetection** and **distortion** in thermal images.
Environment Condition	For example: • Illumination variation • Fog, dost, • High humidity and etc.
Sudden Movements	• **Navigation** algorithms • Flight controller
Motor Vibration	• Camera **stabilizer** • **Damper** installation • Camera with **higher frame rate**

AERIAL INSPECTION

Method Overview

•Inspection time with respect to the surface length between 1hr - 4hr

•Non Linear guidance law

•The UAV follows a waypoint algorithm and inspects specific points of the sample in order to get full coverage

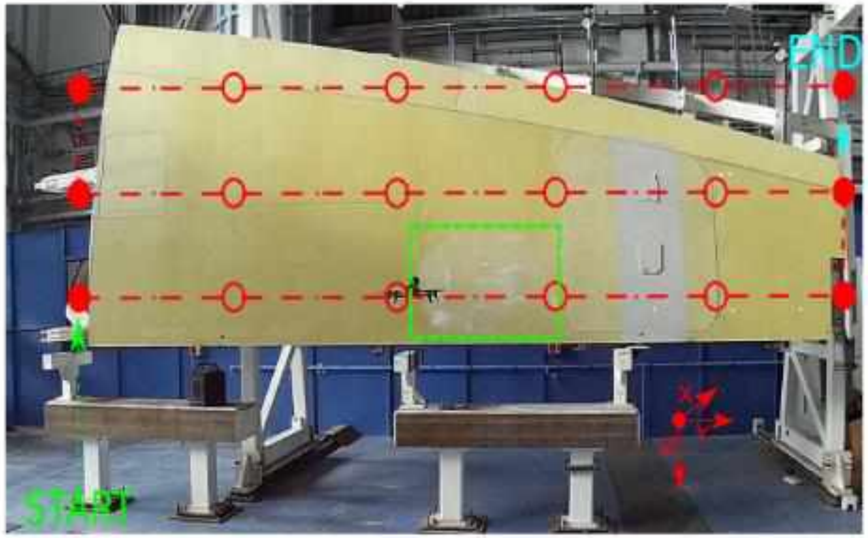


Fig. 5. Automated aerial wing inspection using 18 waypoints.

Detection Algorithm on Metallic Structures: Challenges

The main challenges were:

- Collection of data containing actual defects
- Classify the data containing actual defects and ones containing green coloured areas

Development of the Defects Detection Algorithm: Software overview

Algorithms for defect detection:

‘Classic’ Image processing approach

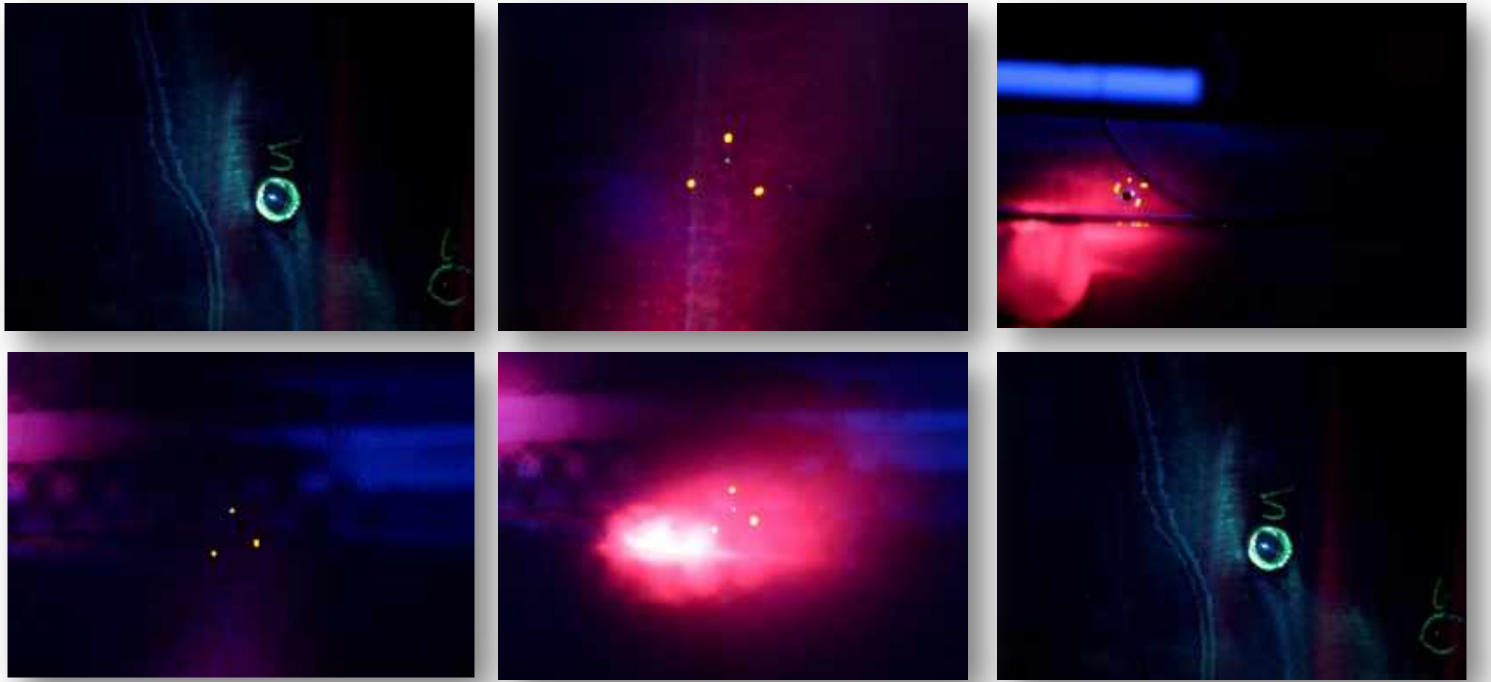
- Step 1: Create the baseline with images containing defects
- Step 2: Filter the images from the inspection to keep only the ones having green areas
- Step 3: Perform an initial comparison between the remaining images with the baseline
- Step 4: Depending on the results of Step 3 perform a second comparison with the baseline

Machine Learning Approach

- Random Forest Classifier

Development of the Defects Detection Algorithm: Create the baseline

11 images from 4 possible defects were chosen as the baseline



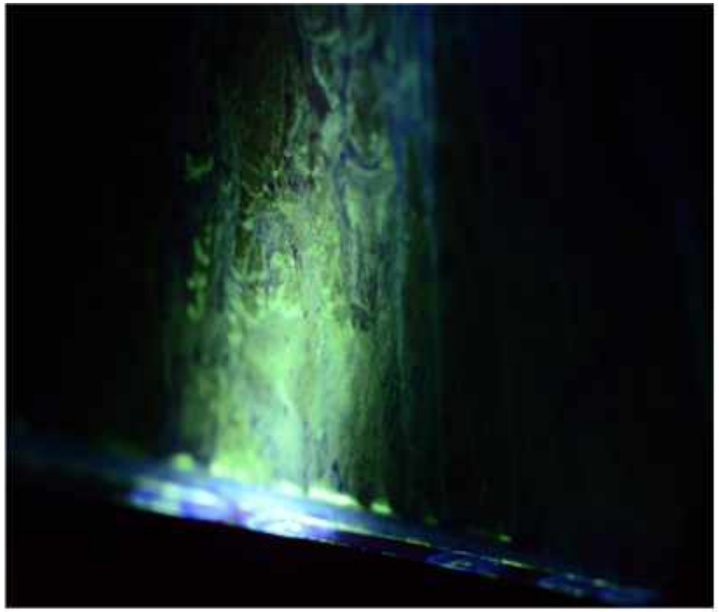
Development of the Defects Detection Algorithm: Image Filtering

In this step the software filters the images and keeps only those containing green colour because:

- The biggest area of the wing panel does not have any fluoresce liquid during inspection
- If these data were processed in the next steps of the software a lot more of computational time and resources will be needed

Development of the Defects Detection Algorithm: Image Filtering

(a) Initial Image containing green areas



a

(b) Image after masking

b

Development of the Defects Detection Algorithm: 'Classic Image Processing Approach'

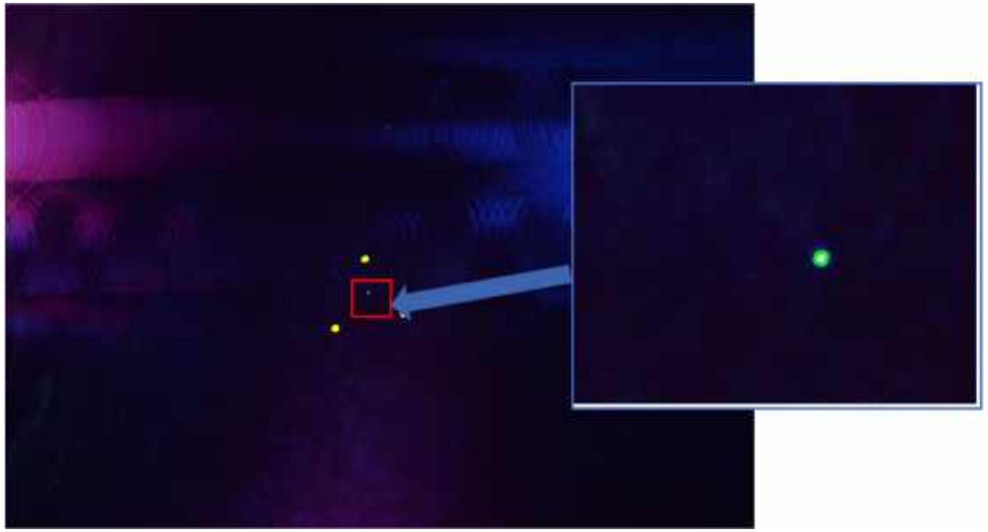
First a comparison comparison with the baseline the algorithm of Structural Similarity Index Measure (SSIM) was used:

Algorithm procedure for the second comparison with histogram

- Each baseline image's histogram is calculated for only the green channel
- Then compared with the histogram obtained from the image from the inspection
- If the outcome value of the comparison is below 0.1 then the image can be classified as an image with a defect

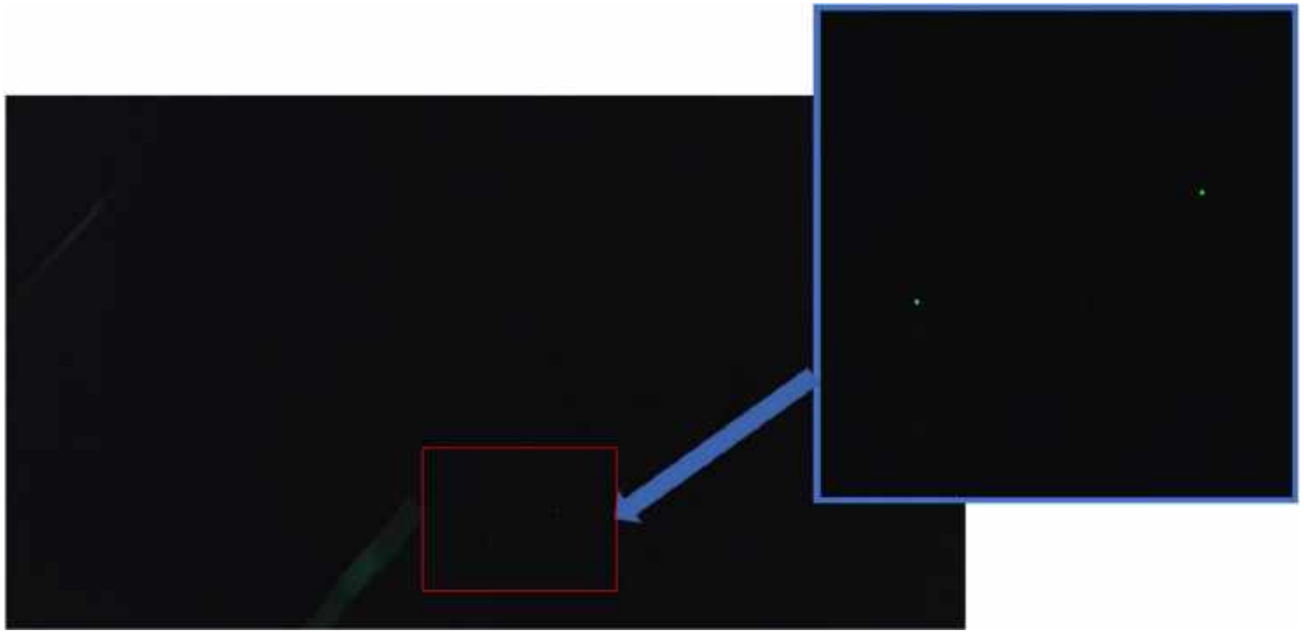
Development of the Defects Detection Algorithm: Results

- Dataset for testing contains 119 images
- 25 images of 4 possible defects
- Algorithm classifies correct all 25 images defects plus one



Development of the Defects Detection Algorithm: Results

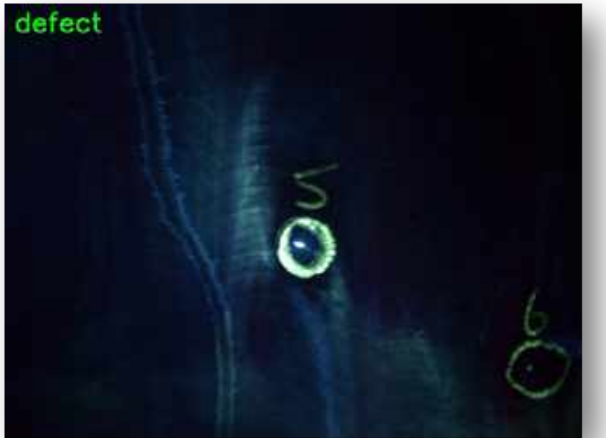
- Wrong prediction. Image is very similar so that why the software has classified it as a possible defect
- As the baseline with defects will get larger these classifications errors will be eliminated



Development of the Defects Detection Algorithm: Machine Learning Approach

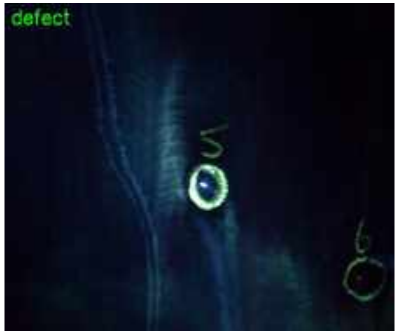
- A Random forest algorithm was implemented
- Trained on the image dataset (total 133, 30 images with defects, 103 non defects)

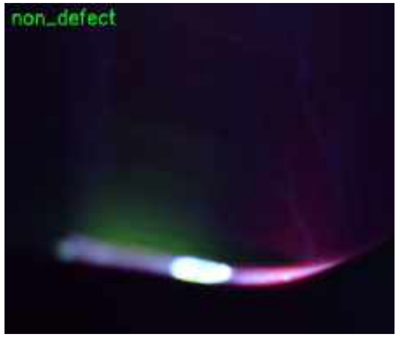
- Features for training, colour and texture
- Results: Accuracy 96%
- Indication that the Random forest approach may work but the dataset is very small

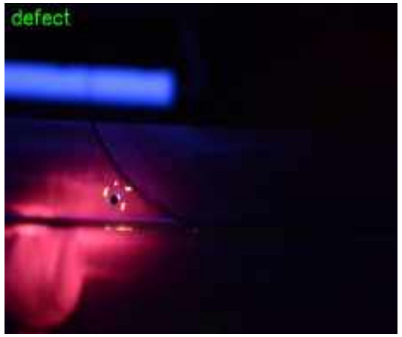


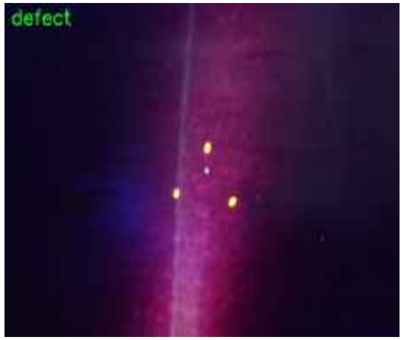
Development of the Defects Detection Algorithm: Machine Learning Approach

Results from Random Forest (5 correct 1 wrong (bottom right))









Development of the Defects Detection on Composites

Overall aim and objectives

- The aim is for a UAV to perform active thermography on aircraft composite structures.
- The UAV will be equipped with an excitation source that is small, light and produces enough energy to penetrate the material.
- Specific algorithms will be developed to process the images to reveal subsurface defects.
- The UAVs will follow path finder algorithms for adequate localisation and good stability.

DJI M210 equipped with thermal camera

Development of the Defects Detection on Composites

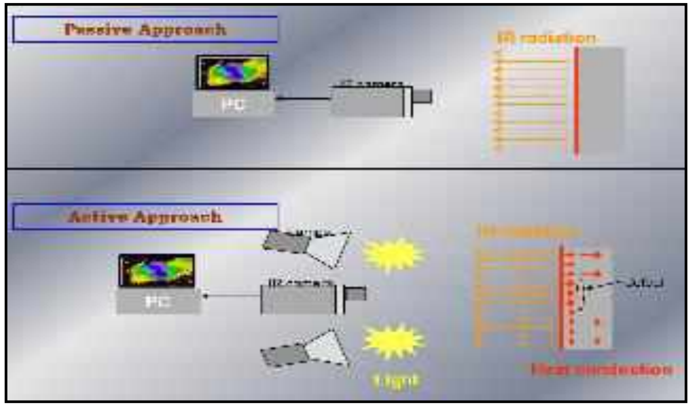
- Carbon Fibre Reinforced Polymer samples.

- FLIR Phoenix IR camera, 3-5 microns, 640x512 pixels and allows data acquisition at 50Hz.

- Data was acquired for 40 seconds with a 1.5 millisecond integration time - 10 frames before the flash, 1990 frames during cooling, a total of 2000 frames.

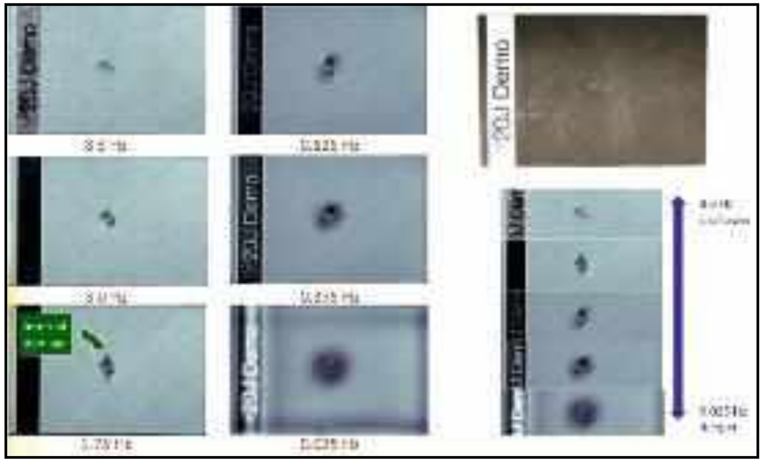
- Data acquired using RDac from FLIR. For signal processing MATLAB and Ir_view from Visiooimage inc were employed.

- 6.400 J per flash using Balcar Xenon flash lamps - pulse duration was 2 ms at FWHM.



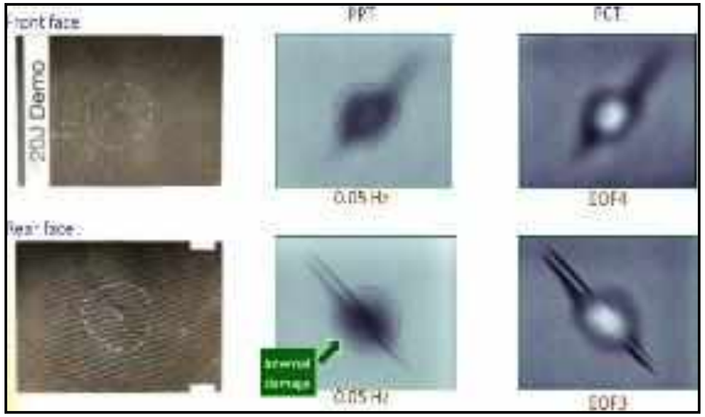
Development of the Defects Detection on Composites

***Sample 20J Demo, Reflection rear face**. PPT. The rear face has some substantial damage. The PPT locates the surrounding internal damage.*

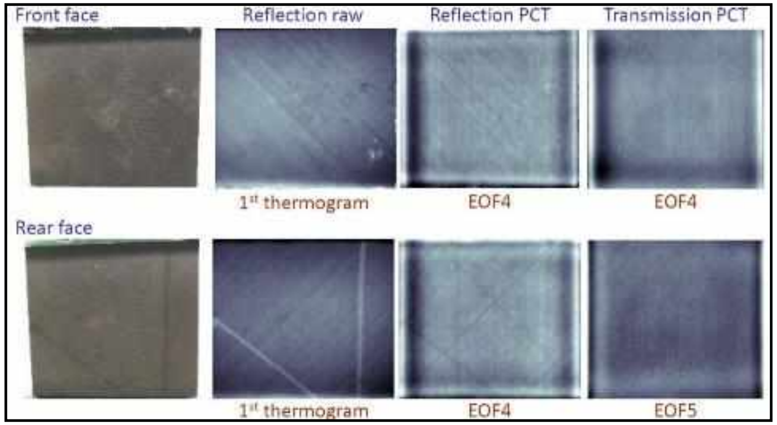


***Sample 20J Demo, Reflection front face, PPT.** The damage is visible on the front face, how, it's clear that the damage is much worse subsurface and spreads further than the impacted area.*

Development of the Defects Detection on Composites



Sample 20J Demo, Transmission. *The test has adequately located the internal damage.*



Sample No Name, Reflection front, back, transmission PCT. *Undamaged composite sample, which was manufactured the exact same way as the 20J sample, the different NDT test prove that this sample is damage-free.*

Cooled vs Uncooled Camera

Cooled Camera
(FLIR Phoenix)

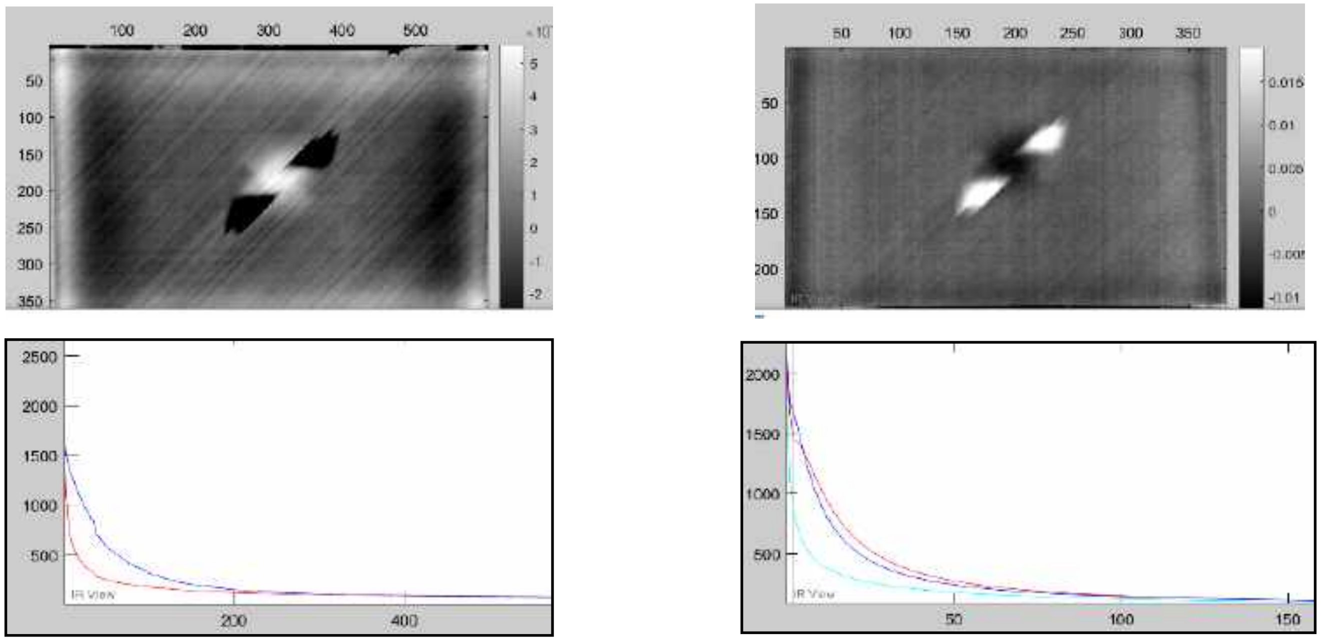
- Spectral Range: 3-5 µm
- Pixels: 640*512
- Frame Rate: 50Hz.

Uncooled Camera
(Jenoptik variocam hr)

- Spectral Range: 7.5-14 µm
- Pixels: 640*480
- Frame rate: 50Hz
- Detector: Uncooled microbolometer focal plane array

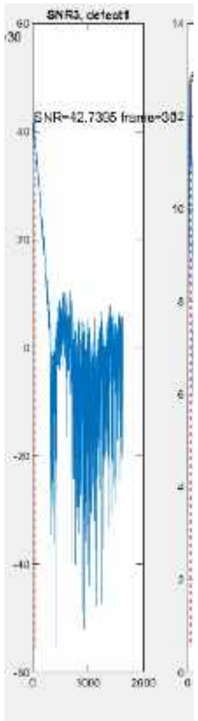
Cooled vs Uncooled Camera

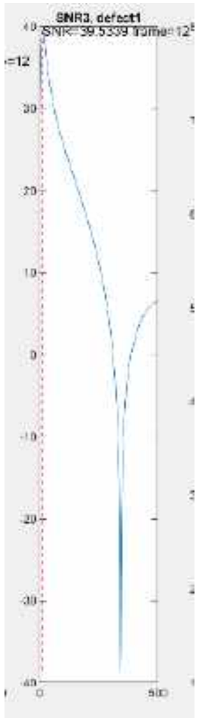
Specimen: 24J impact Damage. Data captured from Rear



Cooled Camera is more sensitive, however the uncooled camera captures sufficient data

Cooled Camera Data - Signal-to-Noise Ratio

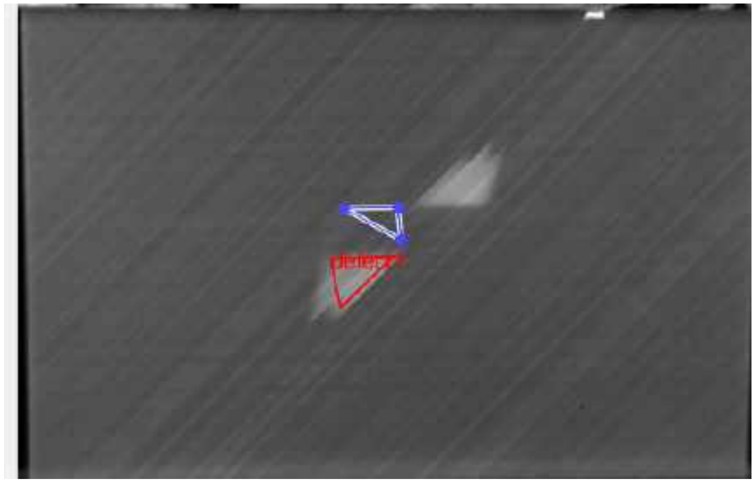




Thermographic Signal Reconstruction

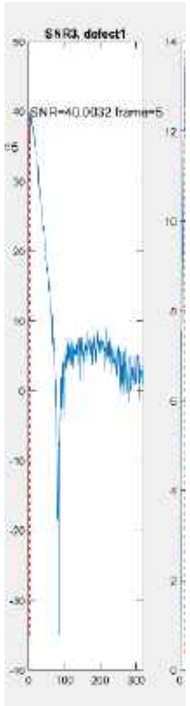
μ_S = Average level of the signal in the defect region of the image
μ_N = Average level of the noise in the reference or sound region of the image
σ_S = Standard deviation of the signal in the defect region of the image
σ_N = Standard deviation of the noise in the reference or sound region of the image

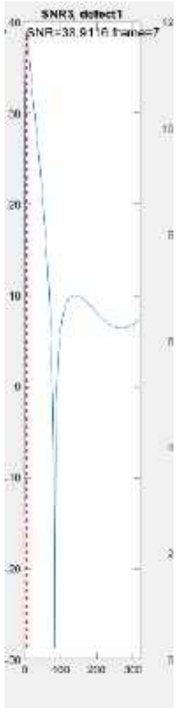
$$SNR_3 = 10 \log_{10} \frac{|\mu_S - \mu_N|^2}{\sigma_N^2}$$



SNR= 39.5339

Uncooled Camera Data - Signal-to-Noise Ratio





Thermographic Signal Reconstruction

μ_S = Average level of the signal in the defect region of the image
μ_N = Average level of the noise in the reference or sound region of the image
σ_S = Standard deviation of the signal in the defect region of the image
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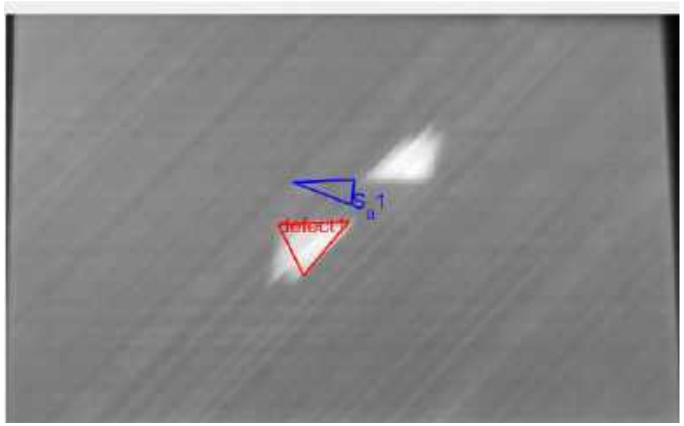
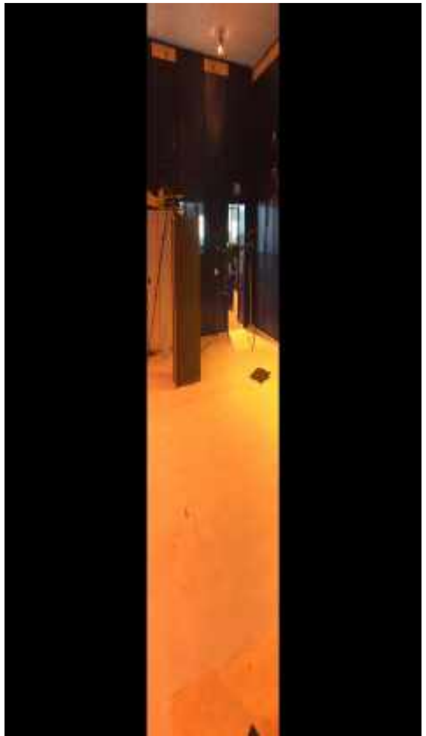
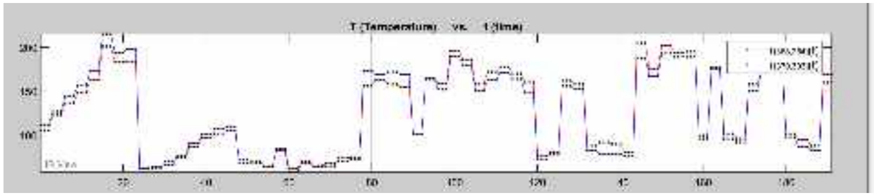
$$SNR_3 = 10\log_{10}\frac{|\mu_S - \mu_N|^2}{\sigma_N^2}$$



SNR= 38.9116

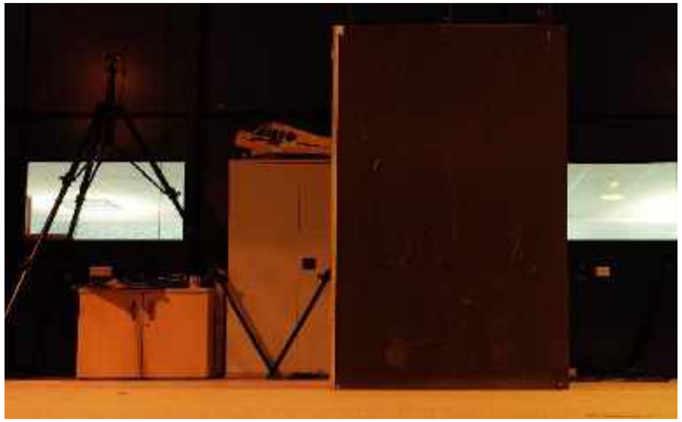
UAV Inspection Trials

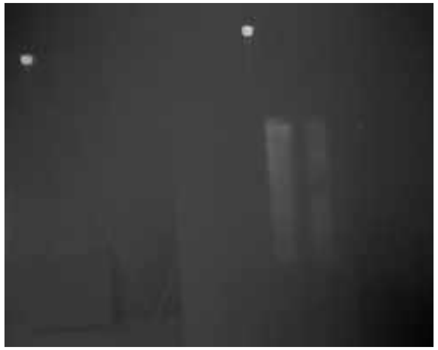




Manually flying a UAV will capture significantly noisy data, that is essentially useless when subject to standard post-processing procedures. This is due to the images being captured at different distances/angles and also the atmospheric interreference. To reduce the noise, the UAV needs to be localised.

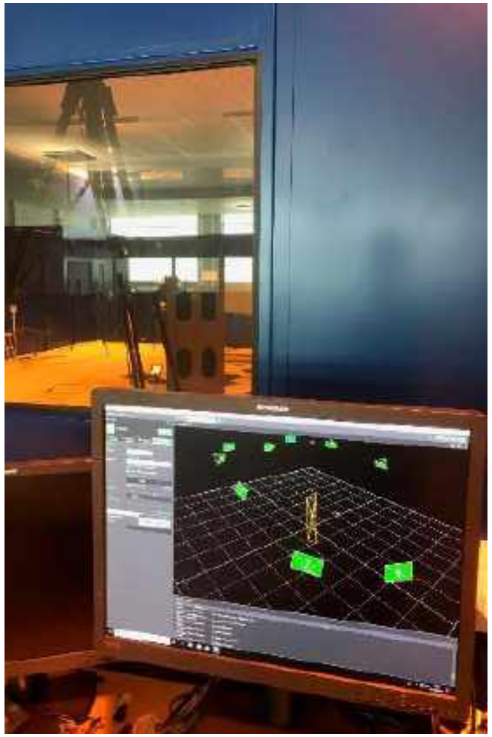
UAV Inspection Trials



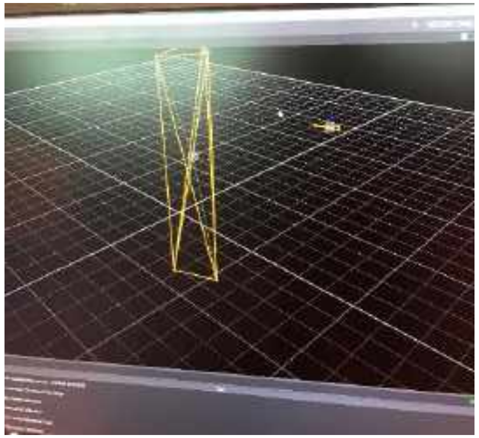


The wing box was excited using hot air, the air was bled into the top left compartment. The images displays a contrast difference which is in fact some debris inside the wing box.
The next experiment will focus on locating different types of subsurface material defects using the following excitation sources; flash lamps & IR heat lamps.

UAV Inspection Trials



The UAV is positionally tracked using a Vicon system, this data is then fed back into the UAV's flight controller so the UAV can localise itself and remain stable, using an algorithm the UAV can be commanded where to fly automatically, allowing a safe and stable inspection.



MultiAcT

Competition: UK and Canada: Enhancing Industrial Productivity (Eureka)

Coordinated by:
Prof Nico Avdelidis

InnoTecUK

Dr Lushan Weerasooriya, Mr Panos Karfakis, Mr Vasilis Tzitzilonis, Mr Menelaos Ioannidis

Cranfield University

Mr Shakeb Deane, Mr Muflih Alhammad, Dr Argyris Zolotas, Dr Luca Zanotti-Fragonara, Prof Antonios Tsourdos

MapAir

Mr Alex Williamson

Canada NRC CNRC

Mr Marc Genest

Université Laval

Mr Parham Nooralishahi, Dr Clemente Ibarra-Castanedo, Dr Hai Zhang, Prof Xavier Maldague

BI Expertise

Mr Youssef Loudiyi, Mr Hobivola Rabearivelo

THANK YOU !!!