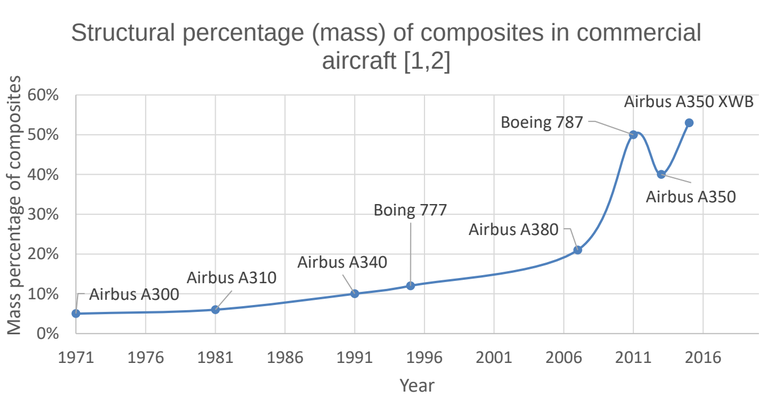
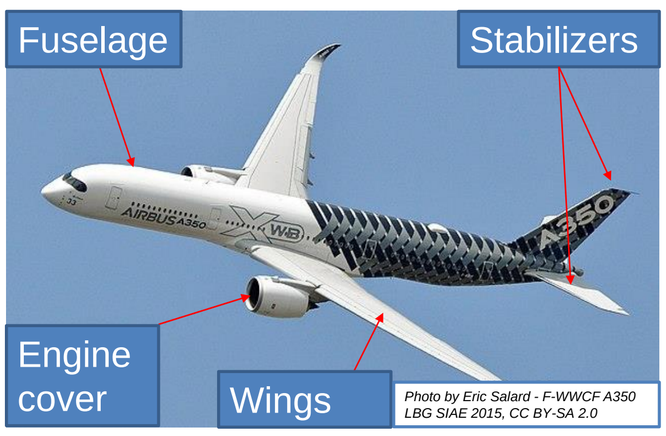
Automated Ultrasound Data Processing for Defect Detection and Characterization Through Machine Learning

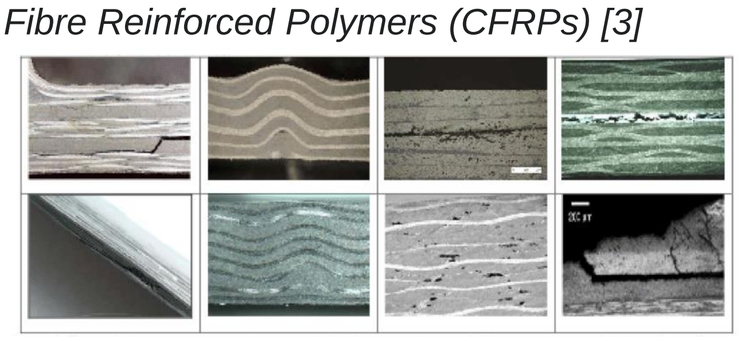
Student: Vedran Tunukovic
Supervision: Dr Ehsan Mohseni, Dr Gareth Pierce, Dr Gordon Dobie, Dr Sandy Cochran

Motivation



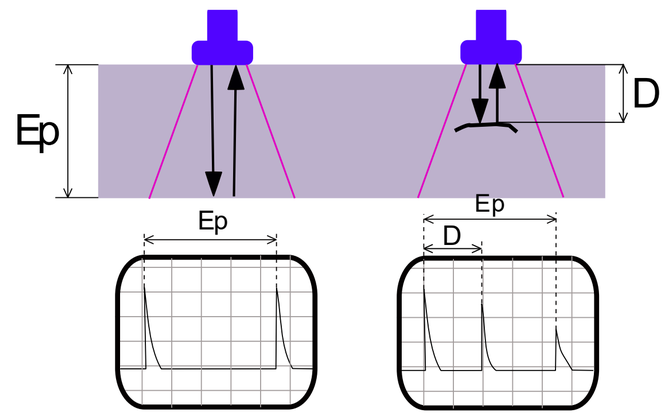


Examples of defects that can occur in Carbon Fibre Reinforced Polymers (CFRPs) [3]

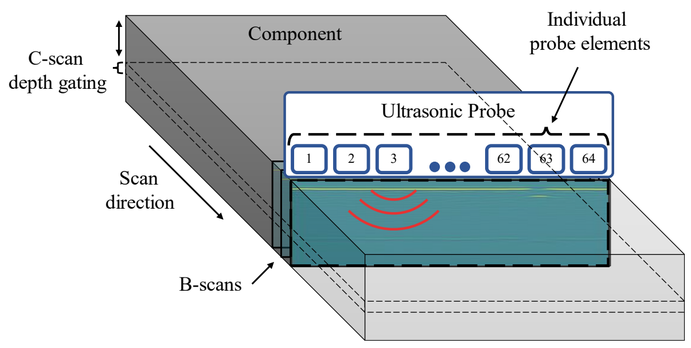


Ultrasonic inspection

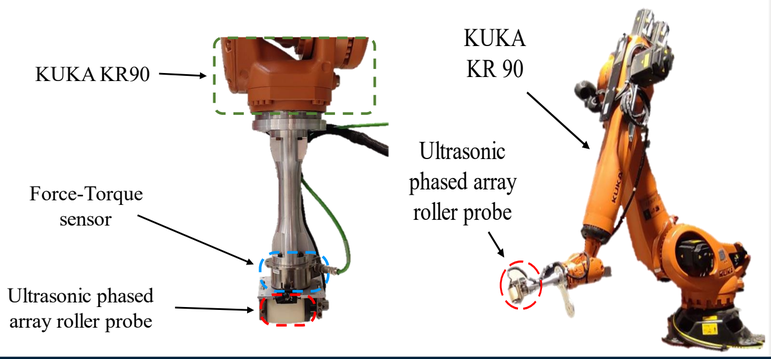
Principle of operation of ultrasonic scanning in NDT [4]



Principle of operation of phased array systems



Robotic arm with mounted ultrasonic phased array



Challenge

Manual inspection is a labour intensive process and reliability is influenced by a human operator

Automatic inspection needs little to no labour, and is precise and repeatable

Data interpretation presents a bottleneck (6 – 8 hours to process data and generate a quality report)

A very large CFRP can be scanned in around 2 hours

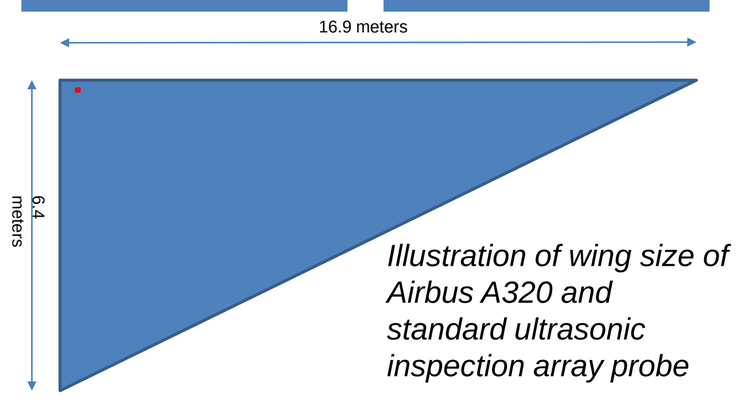


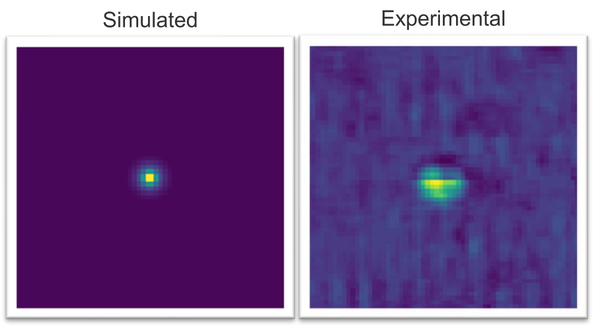
Illustration of wing size of Airbus A320 and standard ultrasonic inspection array probe

Every Machine Learning project starts with data, however:

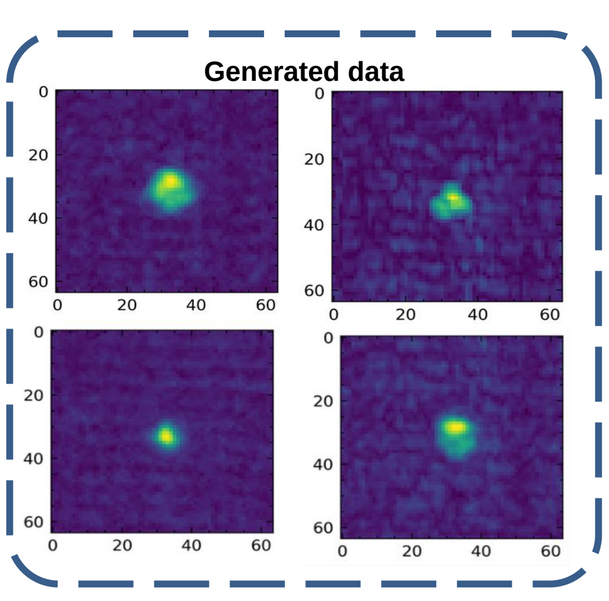
- Large volumes of real defect responses are not available
- Stringent protocols for data protection of civil and military components

Data augmentation

- ML models need to be trained on representative data
- Oftentimes training datasets consist of thousands of data points
- Simulation software does not provide representative data*
- Generative Adversarial Networks (GANs) can help with image-to-image processes



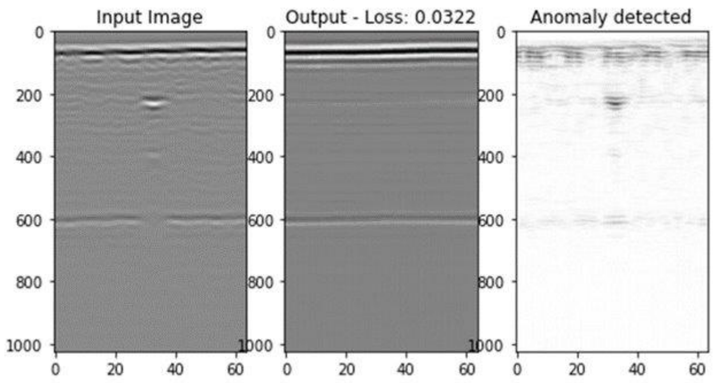
Results from McKnight et al. [5]



Defect detection

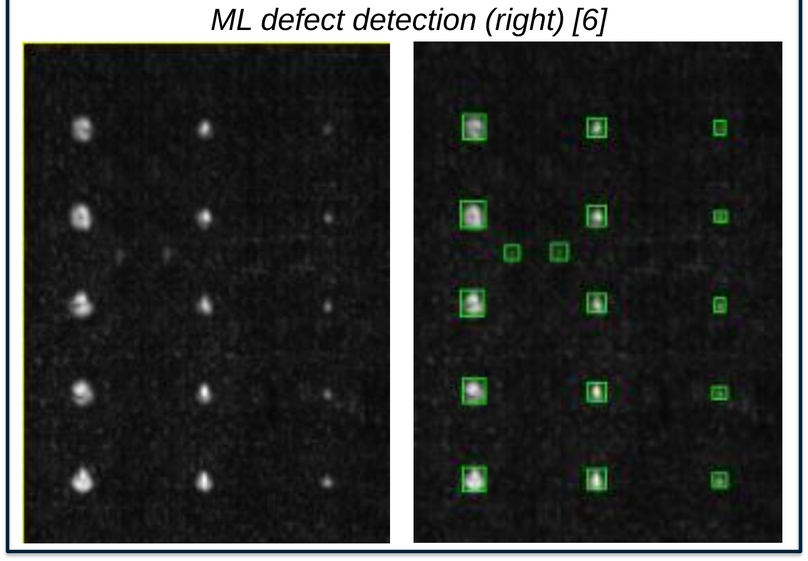
- Unsupervised training performed on healthy B-scans
- ML model tries to reconstruct the original image that is passed through an autoencoding bottleneck
- Defective data is flagged as an anomaly

Examples of anomaly detector performance:



- Supervised training performed on augmented labelled data
- Potential for real-time performance in detection and localisation

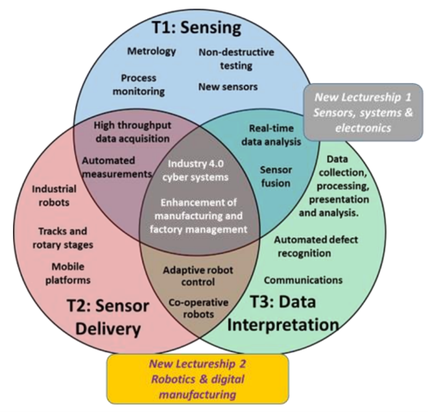
Amplitude C-scan (left) and ML defect detection (right) [6]



Conclusion and future work

- Machine Learning is a powerful tool that can accelerate the process of Non-Destructive Evaluation (NDE)
- Both supervised and unsupervised methods can be applied for defect detection
- Generative algorithms can be used for augmentation and expansion of available datasets

- Future work includes the expansion to multi-class problems (delaminations, porosities, voids...)
- Integration of a multi modal approach where B-scans and C-scans are processed in a single pipeline



References:
[1] Younossi O, Kennedy M, Gräser JC. Military Airframe Costs The Effects of Advanced Materials and Manufacturing Processes [Internet]. 2001 [cited 2022 May 18]. 9 p. Available from: http://www.rand.org/
[2] Slayton R, Spinardi G. Radical innovation in scaling up: Boeing's Dreamliner and the challenge of socio-technical transitions. Technovation. 2016 Jan 1;47:47–58.
[3] Guemes et al., Structural Health Monitoring for Advanced Composite Structures: A Review, DOI: 10.3390/jcs4010013
[4] https://commons.wikimedia.org/wiki/File:UT_principe.svg
[5] Shaun McKnight, Christopher MacKinnon, Ehsan Mohseni, S.G. Pierce, Charles MacLeod, Tom O'Hare: Synthetic data and noise generation approaches including GANs for domain adaption of defect classification of Non-destructive ultrasonic testing [under review]
[6] Vedran Tunukovic, Shaun McKnight, Alistair Lawley, Richard Pyle, Euan Duernberger, Momchil Vasilev, Charalampos Loukas, Ehsan Mohseni, S. Gareth Pierce, Gordon Dobie, Charles N. MacLeod, Tom O'Hare: A study of machine learning object detection performance for phased array ultrasonic testing of CFRPs [manuscript in preparation]

www.linkedin.com/in/vtunukovic/
vedran.tunukovic@strath.ac.uk

SEARCH Sensor Enabled Automation Robotics & Control Hub

University of Glasgow

FUSE CDT Future Ultrasonic Engineering

SPIRIT AEROSYSTEMS

University of Strathclyde Glasgow