# A Robotics-Enabled Eddy Current Testing System for Autonomous Inspection of Heat Exchanger Tubes

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## Proposed Work

**Challenges** for the current testing system:

- The testing process needs well-trained technicians to operate.
- The collected data may be inconsistent due to varying insertion and extraction speeds of the eddy current tester (ECT) probe.
- Decision making essentially relies on the technician's experience instead of taking account of the historical data, thus the decision may not be based on the true status of the tubes.

**Proposed Approach:**

- Developing an imaging system that can identify geometry and locations of heat exchange tubes.
- Developing an adaptive control system that precisely controls the position and motion speed of ECT probes.
- Developing a machine learning tool to facilitate data analysis and real-time decision making for autonomous inspection.
- Evaluating sensing performance of the eddy current tester integrated with the robotic platform.

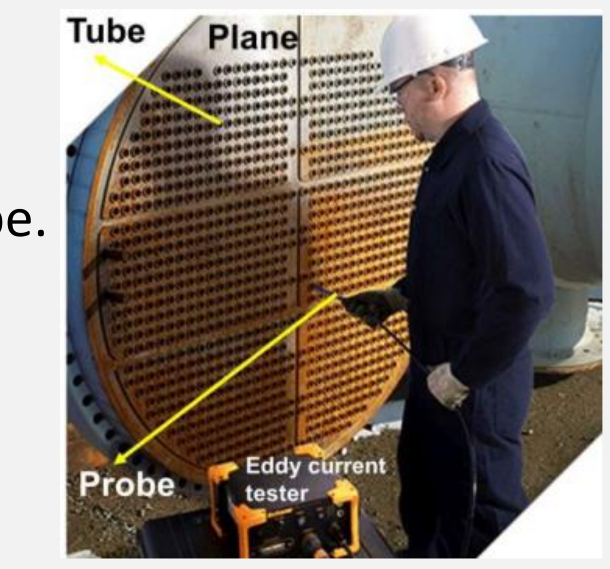


**Figure 1**. Eddy current testing of heat exchange tubes. (Modified from a picture in mistrasgroup.co.uk)

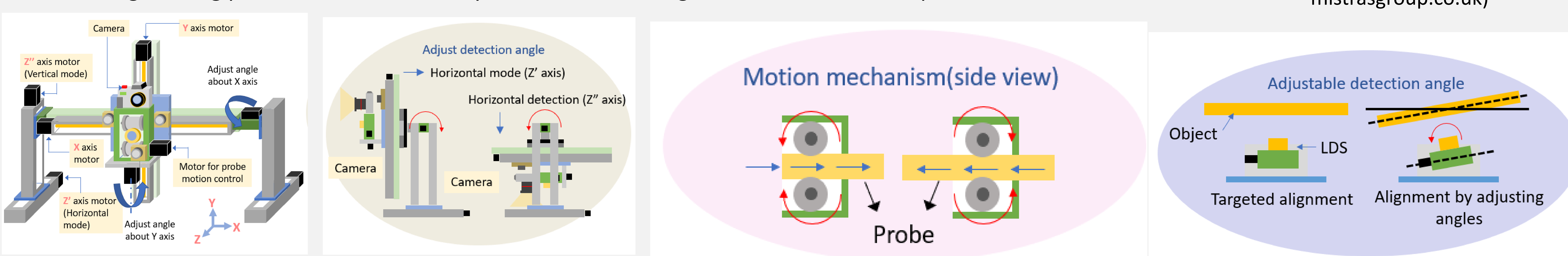


**Figure 2**. Scheme of a robotics enabled eddy current testing apparatus

## Task 1: Image Recognition

**Research Outcome:**

- Developed an image recognition algorithm, which can successfully recognize the different configuration of heat exchanger tube sheet.

**Future work:**

- Calibrate new arrived camera and convert the pixel information to actual location.
- Convert the tube dimension into a moving command and perform the command via computer.

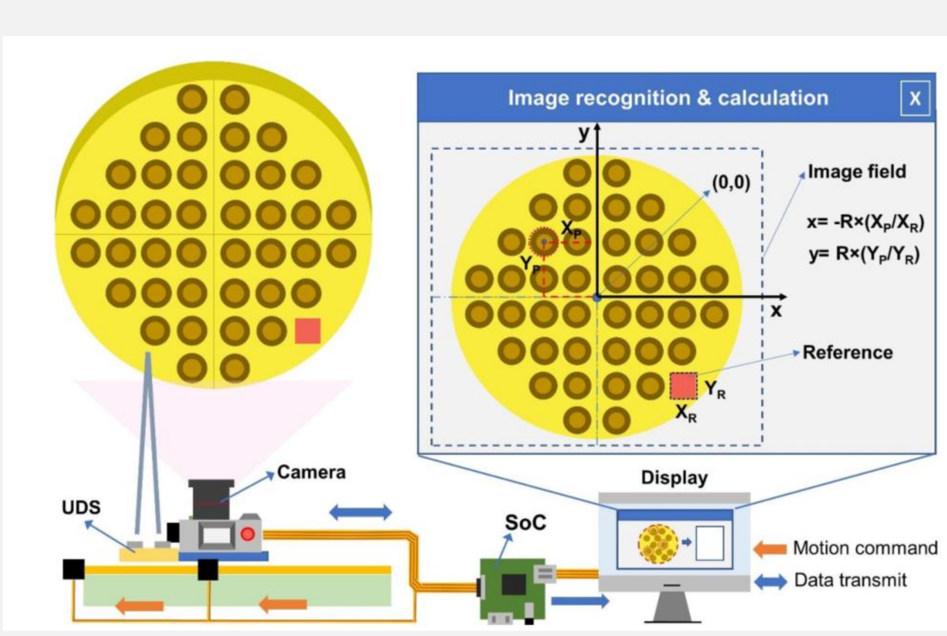


**Figure 3**. Image processing steps for recognizing geometry and location of tubes' inlets.


| | Quantity | Detection quantity | Average radius (a.u.) | Accuracy (%) |
|---|---|---|---|---|
| Case a | 20 | 20 | 13.023 | 100 |
| Case b | 20 | 20 | 15.018 | 100 |
| Case c | 16 | 16 | 14.528 | 100 |
| Case d | 27 | 27 | 13.100 | 100 |

**Figure 4**. The quantification of image recognition result of case a, b, c and d.

## Task 2: Robotic Platform Design

**Research Outcome:**

- update to second version.
- Reduce the number of actuators from 5 to 2 to reduce complexity.
- Add 4WD omni-wheel design to improve mobility.
- Update the new probe holder design – adaptive to different diameter of eddy current probe.
- Perform FEA simulation to confirm the design is reasonable and strong enough to hold all the components.

**Future work:**

- Start to assemble all the components including electronics.

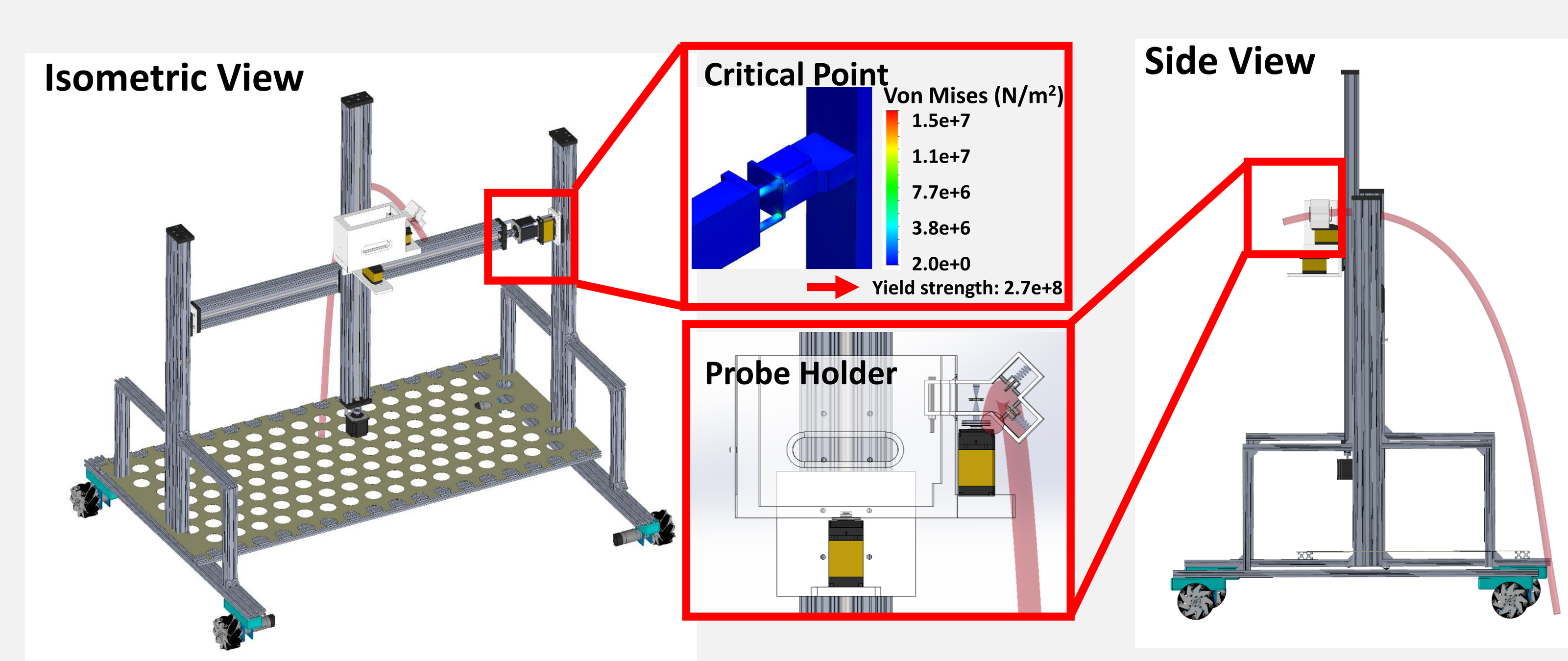


**Figure 5**. Scheme of a robotics enabled eddy current testing apparatus

## Task 3: Machine learning algorithm for classification

**Data:**

- Proposed a data augmentation mechanism using Gaussian mixture distribution to synthesize experimental spectra based on theoretical data for material classification.

**Neural Network:**

- Created a one-dimensional convolutional neural network using a structure similar to Google Inception network for material classification using spectra data.

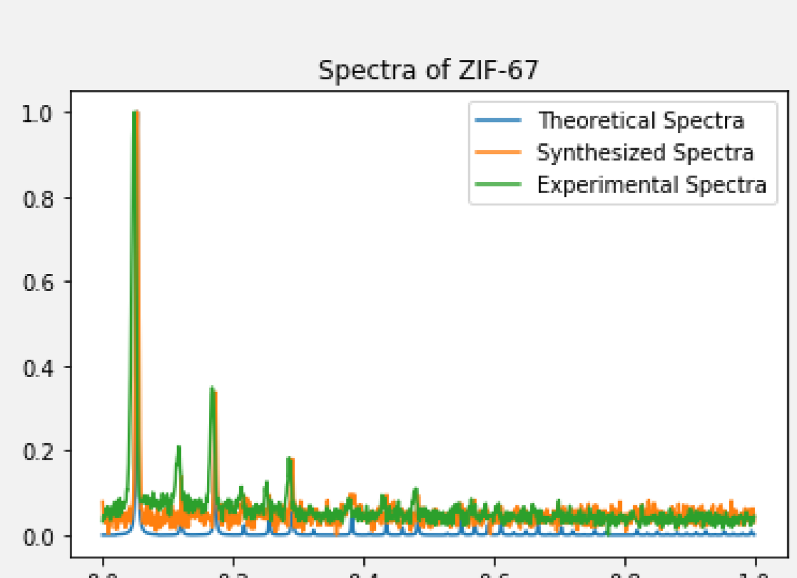


**Figure 6**. Comparison on the theoretical and experimental spectra of a material.

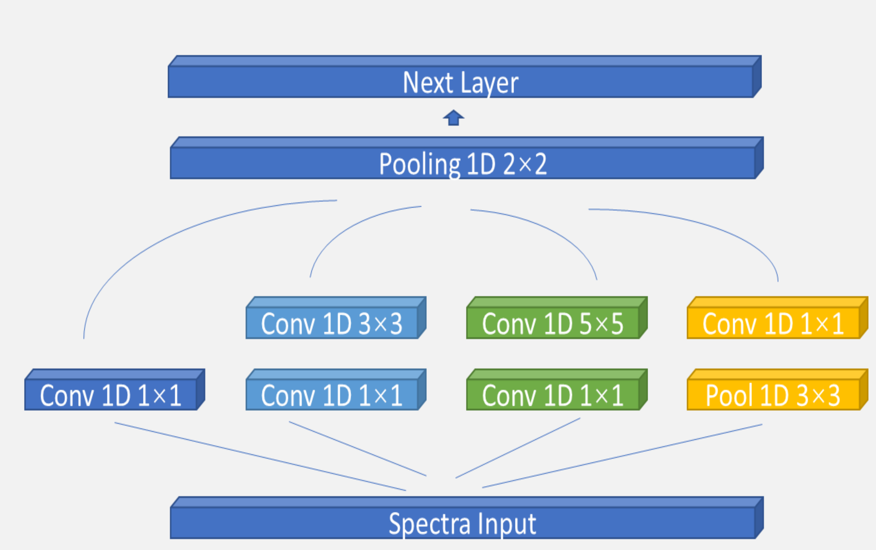


**Figure 7**. Simplified Illustration of Utilized Neural Network Structure.

## Summary

February 2019: research group attended training on demonstration of exchange heat tube cleaning and testing in MU power plant.

**Publication:** Y. Dong, C. Wu, C. Zhang, Y. Liu, J. L. Cheng, and J. Lin. Bandgap prediction by deep learning in configurationally hybridized graphene and boron nitride. ***npj Computational Materials***. 5, 26 (2019).

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