

# ADDRESSING CHALLENGES FOR AUTONOMOUS ROBOTIC FREEFORM EDDY CURRENT INSPECTION VIA COMPUTER VISION ON COMPLEX GEOMETRIES

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## ABSTRACT

Eddy current inspection is a critical method for assessing the health of metallic structures, but it requires precise probe placement to avoid signal variations caused by inconsistent liftoff. Robotic systems enable scanning of complex geometries, maintaining stable liftoff and ensuring accurate data collection. This paper presents a robotic eddy current array (ECA) inspection system that operates without CAD models, using computer vision to reconstruct the part's surface for path planning. Inaccuracies in robot calibration and the reconstructed mesh can disrupt the probe's precise positioning, especially in ECA scanning, where probe tilting increases liftoff variability, particularly at greater distances from the tool's center. To address these issues, we introduce a signal processing technique that reduces the impact of mesh inaccuracies and liftoff fluctuations on the acquired ECA data. The system is validated on curved steel samples with corrosion pits, approximately 50  $\mu\text{m}$  deep and ranging from 1 to 10  $\text{mm}^2$  in area. The results demonstrate the system's effectiveness in detecting defects and its potential for integration into the NDE 4.0 framework.

**KEYWORDS:** robotic NDE, eddy current array, corrosion, computer vision, part surface reconstruction, NDE 4.0

## Introduction

NDE 4.0 is emerging with advancements in technology for managing and processing large datasets, which are crucial for verifying artificial intelligence (AI) systems that interpret these datasets to determine and predict damage (Savin et al. 2024). Various types of NDE robotic systems are being considered for NDE 4.0, including robotic arms and mobile platforms. Recently, several advancements have been made in autonomous scanning of complex-shaped objects using robotic arm platforms. Imaging and reconstruction methods, such as hyperspectral cameras for carbon fiber solutions (Yan et al. 2022) and X-ray for reference-free 3D scanning of defects (Kang et al. 2022; Herl et al. 2020), have been utilized in these systems. In the realm of robotic NDE data acquisition, advanced systems using in-process freeform scanning via ultrasonic testing—synchronizing NDE acquisition with path planning—have been reported (Mineo et al. 2022). Additionally, a freeform robotic arm platform for ultrasonic inspection of complex-shaped carbon fiber samples was recently developed (Hamilton et al. 2024).

Historically, techniques such as laser-based profilometry (Doyle 1995), ultrasonic profiling (Zhen et al. 2018), and physical touch-probes (Lee and Cho 2012) have been employed to assess true surface geometry and adapt scans accordingly. These methods have proven effective over decades, providing precise surface location data for applications requiring stringent geometric fidelity. However, these approaches often involve additional hardware complexity, require contact or near-contact with the surface, or are less suited for large-scale automation in NDE 4.0 applications. An example of merging robotic systems with AI technology is the use of gripper robotics for inspection, employing electromagnetic acoustic transducers (EMAT) scanning and deep learning for pipe assessment (Hespeler et al. 2024). Computer vision (CV) offers a noncontact, scalable, and hardware-efficient alternative for capturing and reconstructing part geometries, particularly for complex or variable surfaces. This makes it more adaptable to modern NDE frameworks, such as NDE 4.0, where automation, flexibility, and integration with AI-driven systems are essential.

Recent developments in eddy current array (ECA) robotic systems have introduced several innovative approaches. Many of these systems utilize a rotary axis, allowing the robot to move the ECA probe along a rotating cylindrical sample. One such system was used for inspecting nuclear assets (Foster

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et al. 2022). Another approach involves a robotic system with flex probes designed to inspect complex structures; however, this system is limited to movement along a single axis (Zhang et al. 2020). In a more advanced example, an aircraft wing was inspected using a CAD model for path planning (Morozov et al. 2018). However, this method often requires reverse engineering the complex structure to obtain the CAD model, which can be time-consuming and resource intensive. Mobile systems have also seen innovation, with repair and crawler robots developed for inspecting power plant boilers (Shi et al. 2021). Additionally, quadruped robotic platforms have been introduced, offering diverse inspection capabilities for energy-producing infrastructure (Tsenis et al. 2024). For in-line pipe inspections, endoscopic laser profiling combined with machine learning techniques has been used to detect deformations within pipes (Mukherjee et al. 2022).

Freeform robotic inspection methods allow for autonomous surface scanning across a wide range of components, including those with curved or complex geometries. By using a reconstruction device, path planning can be performed on a mesh within a virtual environment, eliminating the need for a CAD model. This approach supports robust scanning procedures without the need for reverse engineering components for evaluation. Additionally, it facilitates the alignment of the reconstructed scanning environment with the automated surface scanning system. With these models, a scanning path can be generated, simulated, and then implemented on the physical robot. However, challenges arise when precision scanning is required for specific NDE methods and applications.

In this work, sub-millimeter depth corrosion damage on curved steel samples is detected and characterized using eddy current testing (ECT). ECT requires maintaining a consistent liftoff between the probe and the conducting surface. A small liftoff is essential to generate sufficient eddy currents in the test sample, ensuring a high signal-to-noise ratio (SNR). Furthermore, maintaining a constant liftoff is crucial for minimizing data variability, which can introduce uncertainties and complicate data processing. These challenges are amplified when inspecting small corrosion damage, as the ECT probe must be finely calibrated for high-frequency precision scanning. The tilt of the ECT sensor can also reduce defect detectability, as the magnetic field is affected by the sensor's angle during field inspections. The worst-case scenario occurs when a collision happens due to inadequate inspection path planning for complex-shaped test samples, potentially damaging the probe immediately or through scraping along the rough or irregular surface.

Optimal NDE path planning can be developed in a virtual environment before being applied in physical space. However, discrepancies between the virtual model and the test specimen can lead to improper probe orientation relative to the scanned surface. For instance, if the model is not correctly aligned with the physical specimen, it can cause variations in probe rotation and liftoff throughout the scanning path. Additionally, geometric differences may arise between the virtual reconstruction

and the actual part. While reconstruction devices like structured light provide sub-millimeter accuracy, errors can accumulate for larger specimens. CAD models may also fail to account for small geometry variations introduced during manufacturing. Finally, errors in calibrating or mastering the robotic joints can result in misalignments in Cartesian space, affecting the positional accuracy of the scan.

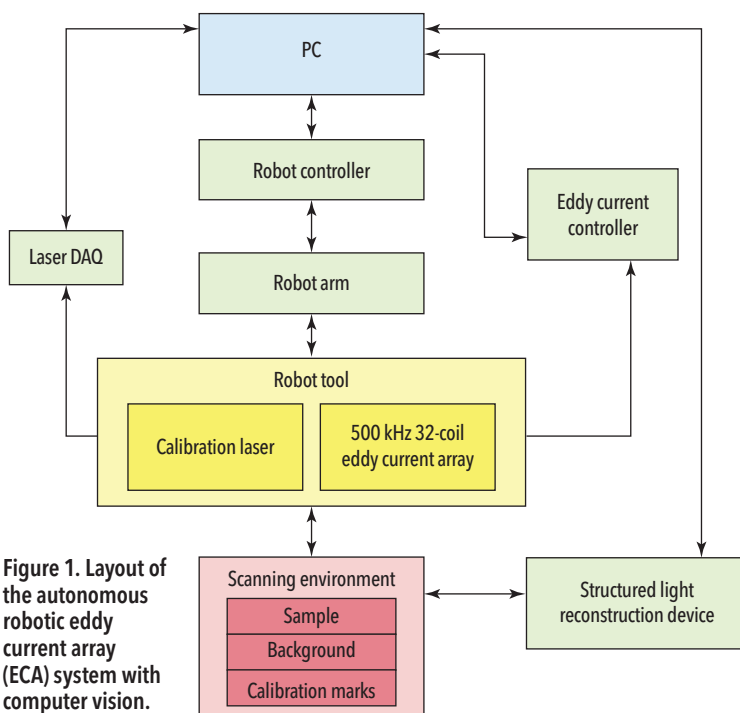
This work addresses key challenges and demonstrates the capabilities of robotic ECT using array probes for surface corrosion characterization on curved steel samples. The robotic system presented here features an ECA probe that enables rapid scanning and provides expanded surface coverage through multiple coils or channels. It also employs CV-based path planning to perform inspections without relying on CAD models, representing a significant advancement in automation and digitization within NDE 4.0. Furthermore, we introduce the integration of robotic inspection with real-time data processing techniques, such as detrending algorithms and synchronization error mitigation, ensuring consistent detection of surface corrosion as shallow as 50  $\mu\text{m}$ , despite challenges such as liftoff variations and probe orientation errors.

## Materials and Methods

This section outlines the methodology for preparing curved corrosion samples with simulated damage and details the experimental setup for robotic ECA inspection.

### Robotic Setup for NDE Using ECA and Computer Vision

A block diagram of the robotic ECA system is shown in Figure 1. The system consists of an industrial robotic arm with 6 degrees of freedom (DOF). Communication between the PC and the robot controller is established via C#, with movement



**Figure 1.** Layout of the autonomous robotic eddy current array (ECA) system with computer vision.

instructions issued and real-time Cartesian position and orientation data received at a frequency of approximately 70 Hz through an Ethernet connection. The system integrates three key sensors: (1) a structured-light (SL) camera, (2) a calibration laser profilometer, and (3) an eddy current array (ECA).

The structured-light camera with a reconstruction accuracy of 0.1 mm is positioned remotely from the robot as shown in Figure 2a. It captures the part's geometry, enabling precise path planning. The calibration laser profilometer is mounted in a custom 3D-printed holder, as illustrated in Figure 2b. This sensor ensures proper alignment between the reconstructed virtual model and the robot's physical workspace. Capable of measuring depths ranging from 50 mm to 150 mm with an accuracy of 4  $\mu\text{m}$ , the sensor is positioned 60 mm from the calibration regions of the test specimen.

The ECA used in this system is an array of 48 pancake coils fabricated on a flexible substrate. The ECA is interfaced with the PC using the multichannel eddy current data acquisition system via a software development kit (SDK) in C#. Although the probe is a flexible array, it is mounted on a rigid fixture to ensure consistent and known coil orientations during operation. While the probe's nominal center frequency is 500 kHz, it is operated at 2 MHz to provide maximum sensitivity to surface corrosion. The array consists of 48 coils arranged in three rows of 16, with a 1.25 mm spacing between coils, offering a total coverage width of 34 mm, as shown in Figure 2c. During data acquisition, only the right two rows of 16 coils are used, resulting in a total of 32 active sensors.

In the system, the ECA supports two operational modes: impedance (absolute measurements) and reflection (pitch-catch). A differential mode is also applied during post-processing using MATLAB. The coils are driven by a 5 V AC signal, producing complex voltage outputs, with the real component used for post-processing. The robot is programmed to position the ECA probe 1 mm above the test surface, though variations in liftoff can be observed during experiments.

The laser and ECA probe integrated into the robotic setup are depicted in Figure 2b. Eddy current measurements are

acquired at an update rate of 16 kHz per coil. This configuration provides a spatial resolution of 50  $\mu\text{m}$  along each raster line, ensuring sufficient detail for effective corrosion detection.

### Scan Path Generation for ECA

The scan path generation procedure is adapted from the framework outlined by Hamilton et al. (2024), beginning with the virtual reconstruction of the scanning environment using a structured-light camera to create a digital model of the part. This virtual model is aligned with the physical workspace through calibration points identified by a laser calibration sensor. Accurate alignment is ensured by comparing the physical calibration points in the robot's workspace with their virtual counterparts using point-to-point projection. The reconstructed mesh is further refined by segmenting the sample from the background and applying decimation and Laplacian smoothing techniques (Sorkine et al. 2004). A zigzag raster path is then generated on the refined mesh using a ray-plane intersection array algorithm (Hamilton et al. 2024), achieving a point cloud resolution of 0.1 mm  $\times$  0.25 mm, which is interpolated to 0.2 mm  $\times$  0.2 mm for 2D processing. This path is simulated and converted into robot commands. During the scanning process, the system PC gathers data streams from the ECA, alongside real-time orientation data from the robot's tool frame. These data streams are processed to ensure accurate and reliable defect detection.

The system utilizes two types of scanning paths. The first, referred to as a "fast scan," involves the array coils scanning the region of interest without redundancy. In this method, the array probe traverses the test sample only once along its long side, minimizing scanning time in proportion to the number of coils in the array. For higher resolution, sub-scans can be performed, where the pathing distance of a coil is smaller than the spacing between adjacent coils.

The second scan type, referred to as a "full scan," introduces redundancy by using a single coil to collect data instead of the entire array, ensuring more detailed coverage at the cost of increased scanning time.

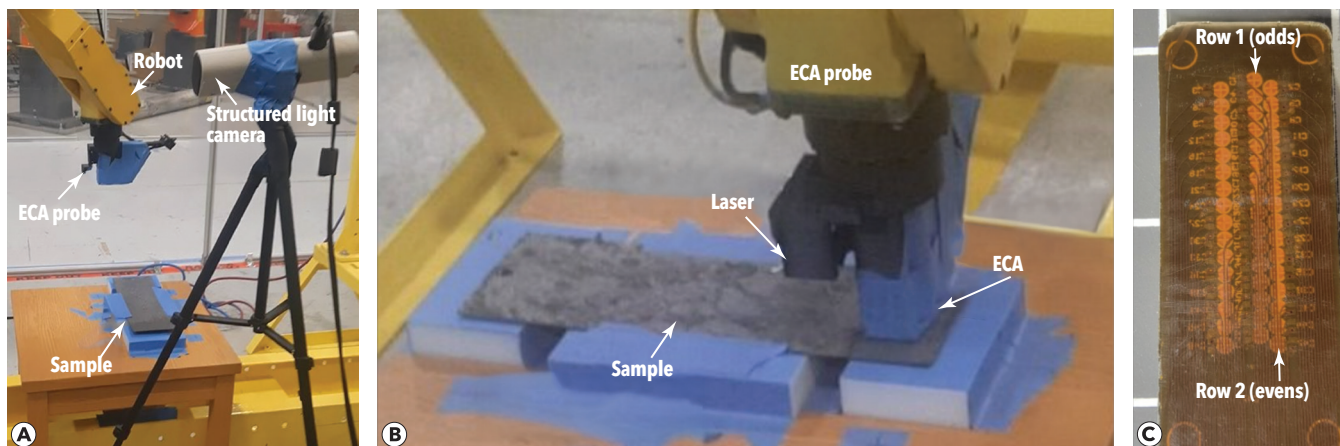


Figure 2. (a) ECA robotic setup, showing a sample, the robot tool-frame lifted away from the sample, and the structured-light camera facing the sample, outside the robot's workspace; (b) ECA robotic scan on the sample; (c) ECA probe view from below.

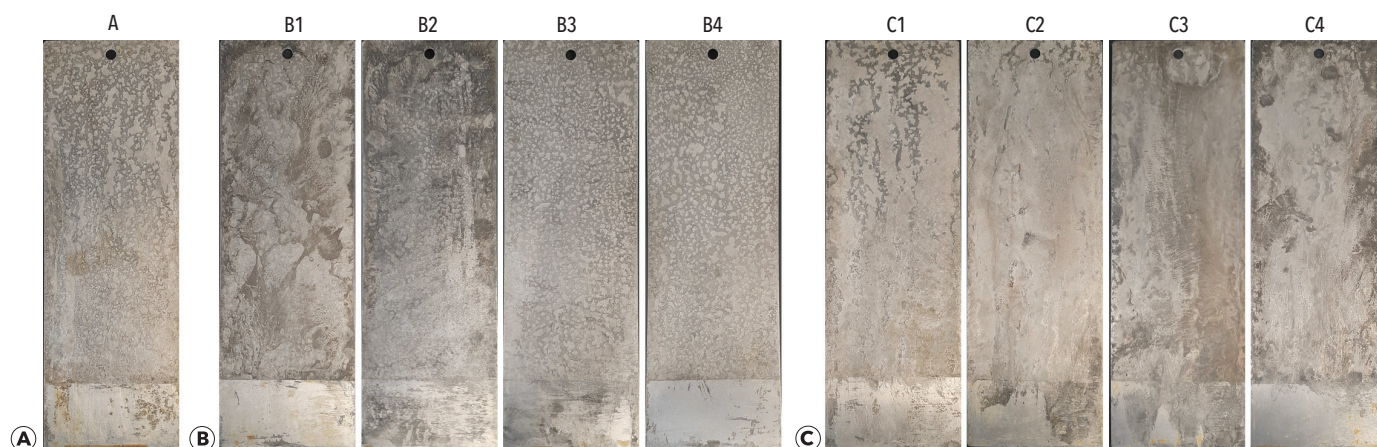


Figure 3. Steel samples with corrosion damage: (a) flat sample A; (b) concave samples B1-B4; (c) convex samples C1-C4.

**TABLE 1**  
Curvatures of test samples with corrosion damage

| Sample              | A     | B1    | B2    | B3    | B4    | C1    | C2    | C3    | C4    |
|---------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Curvature $k$ (1/m) | 0.000 | 0.304 | 0.397 | 0.527 | 0.842 | 0.304 | 0.451 | 0.528 | 0.842 |

### Preparation of Steel Samples with Corrosion Damage

A total of nine steel samples, each measuring 12 in.  $\times$  4 in. (30.5 cm  $\times$  10.2 cm) were prepared for corrosion inspection using the robotic ECA setup. The samples included three distinct geometries: one flat, four concave, and four convex, as shown in Figure 3. These shapes were achieved using a sheet roller, with curvatures designed according to corrosion standards detailed in Table 1. After shaping, the samples underwent a seven-day salt spray corrosion process in accordance with ASTM B117-03 (ASTM 2003). To create a calibration area for the ECA, the bottom inch (2.54 cm) of each sample was treated with a corrosion inhibitor; however, some corrosion leached into this section. Residual rust was removed using a soaking solution.

### Comparison of Processed ECA Data with Microscope Depth Profiling

Ground truth volumetric data of surface corrosion were obtained using a high-resolution digital microscope for comparison with the ECA data. To locate the defects, 2D cross-correlation was applied, in which the microscope data was searched across the ECA data. The best matching pattern was indicated by the maximum correlation value between the two sets. The patterns from ECA voltages correlated well with the depths of the microscope data.

### Challenges in Robotic ECA Inspection of Curved Samples

Detecting fine surface or underpaint corrosion defects (e.g., 50  $\mu$ m deep) on curved metallic surfaces using robotic arms

is challenging due to strict liftoff, tilt, and thermal stability requirements for the ECA probe. For example, ECT typically necessitates maintaining a close and constant liftoff (e.g., 1 mm) between the coil probe and the metallic surface. Small liftoff ensures a noncontact testing method, maximizing the induction of eddy currents and achieving a high signal-to-noise ratio (SNR) for the measurements. Additionally, surface corrosion detection often requires sensor coils to operate at excitation frequencies in the MHz range. As a result, probe misalignment and temperature fluctuations can introduce errors during the scanning process, affecting both defect detection and the accurate quantification of defect depth. This section explores the challenges faced during robotic ECT and presents typical experimental images obtained using the proposed robotic NDE system with computer vision.

### Effect of Inconsistent Probe Liftoff and Tilt on ECA Measurements

Inconsistent liftoff typically introduces low spatial frequency trends that overlap with defect indications, complicating image processing and defect detection. Robotic manipulators can also introduce inconsistent sensor tilt, affecting the distribution of the excitation magnetic field from the coil sensor. For the rigid and linear array probe, orientation errors affect each coil as a body transformation, with coils at the edges of the array having a different liftoff compared to the coils in its center. Improper liftoff and/or tilt of the ECA probe can not only disrupt measurements but also cause collisions with the test part, potentially leading to immediate damage to the probe or long-term degradation if dragged over rough surfaces.

Liftoff and tilt inconsistencies often result from issues in the reconstruction and registration of the virtual geometry for path planning, such as misalignments between the virtual and physical surface geometries. Additional factors include limitations in the robot's hardware and the synchronization between the ECA data acquisition instrument and the robot. While post-processing methods can help mitigate these errors and improve defect detection, some defects may still be missed if the errors exceed the algorithm's corrective capacity.

### Part Surface Reconstruction Error

Errors in the reconstructed surface of the test specimen can arise from several sources. One common issue is the alignment of the model, where misalignments lead to translation errors along the scan path. If the model is not properly oriented with its physical counterpart, rotation and liftoff variations will occur throughout the entire scanning process. Another challenge is the discrepancy between the virtual model and the physical surface geometry.

In this work, surface reconstruction of steel samples is achieved using structured light with a CR-01 scanner offering 0.1 mm accuracy. However, metallic surfaces can reflect light, causing inaccuracies during scanning, a problem that can be mitigated using blue-light reconstruction (Zhan et al. 2015). Additionally, errors may arise if the sample lies outside the sensor's effective range, affecting both translation and rotation. Ray-plane intersection algorithms calculate translation and rotation based on the mesh faces' normal directions (Hamilton et al. 2024).

Rotational errors between scan points can introduce discrepancies, which can be mitigated using detrending algorithms applied to the raster path. These errors arise at various stages, as illustrated in Figures 4a and 4b from a scan of flat Sample A (Figure 3a). Figure 4a depicts the delta rotation acquired from the robot alone, revealing a baseline pathing error. In raster pathing, certain scan lines shift more than others due to orientation errors on the mesh. Figure 4b highlights spatial variations in the ECA signal caused by positioning errors from pathing inaccuracies.

Mesh registration also introduces potential body transformation errors. The process, which relies on point-pair picking (PPP), aligns the mesh within the robot's reference frame. Misalignment in laser calibration or displacement of calibration marks during sample placement can introduce errors, as can human inaccuracies in selecting calibration points. To reduce these errors, the root-mean-square (RMS) error was minimized to approximately 1 mm. Although PPP provides an initial approximation, body errors were further corrected using 2D detrending. Figure 4c illustrates this correction with four calibration markers (R0–R3), whose reconstructed positions were compared to physical locations identified via laser calibration. The overall RMS error across all four points was 0.516 mm.

### Robot Mastering Error

This error occurs during the calibration of a robotic arm's joints, where each joint requires precise alignment at zero degrees. While state-of-the-art robots automate this process, the robotic arm used in the presented system relies on manual measurements and markings on the robot itself. Consequently, sub-degree misalignments can occur at each joint. Although these errors may seem minor, they result in more complex orientation discrepancies within the robot's joint system,

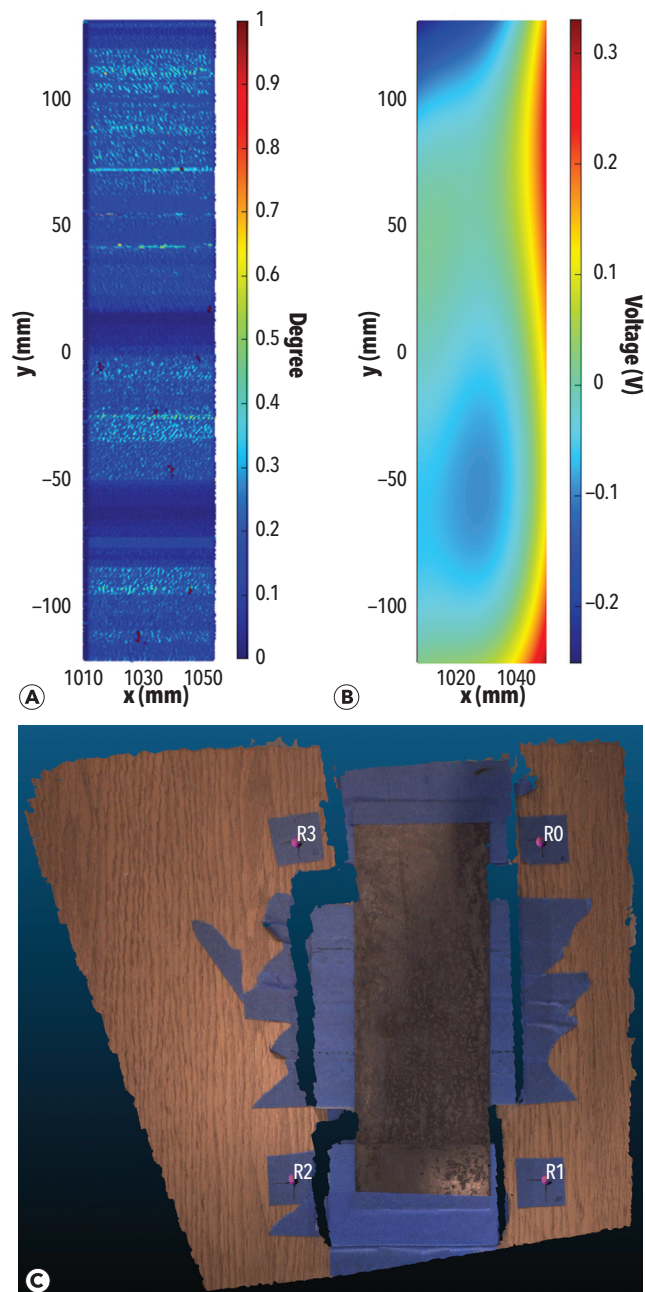


Figure 4. Effects from mesh pathing errors: (a) changes of rotation  $xyz$  of the probe during the scan of flat Sample A as provided from the robot controller; (b) corresponding voltage trend registered by the ECA; (c) aligned scanning environment from structured-light reconstruction after selecting point pairs on the flat sample.

particularly affecting the Denavit–Hartenberg (DH) parameters rather than the Cartesian coordinate system, as seen with other error types. These calibration inaccuracies manifest as “wave-like” patterns, introducing approximately 1 mm of spatial variance in the ECA scans (see Figure 6a). To mitigate this issue, a specialized post-processing method was developed.

### Synchronization Error Between Eddy Current Instrument and Robot’s Controller

Errors arising from poor synchronization between the robot’s real-time orientation data and the real-time acquisition of the scanning instrument must also be considered. These synchronization issues cause smearing due to lag between the two data streams. The system managing both data flows—comprising the robot’s controller and the ECA data acquisition instrument—operates as two separate systems, leading to inevitable delays. Although timestamps are recorded alongside each data stream, a nonconstant delay persists between the two. On average, this delay was found to be approximately 50 ms. To minimize the effects of this delay, slower scan speeds of 25 mm/s were employed, reducing smearing to under 1 mm, which was adequate to detect most corrosion flaws.

### Signal Fluctuation Due to Coil Heating and Environmental Effects

When performing NDE using ECT array probes in absolute mode, voltage fluctuations are occasionally observed that are unrelated to probe orientation. These fluctuations may occur even when the probe is stationary. Such behavior is typically attributed to high excitation currents in the coils or ambient temperature changes (García-Martín et al. 2011). For instance, Figure 5 illustrates a pronounced case of voltage drift in an ECA probe while it remains stationary 1 mm above the

sample. This drift occurs during the coil warm-up phase after powering on the ECA data acquisition system, prior to reaching its steady-state operating temperature. In this case, the coils were driven at twice the maximum recommended voltage, and the signals were amplified by 60 dB. Additionally, the robot, ECA probe, and steel test sample with corrosion damage were situated near a high-power air duct emitting hot air into the adjacent lab space. Once the coils reached their steady-state temperature, the ECA probe was nulled on an undamaged region of the test sample. After calibration, voltage variations were reduced to a range of  $-0.015$  V to  $0.015$  V.

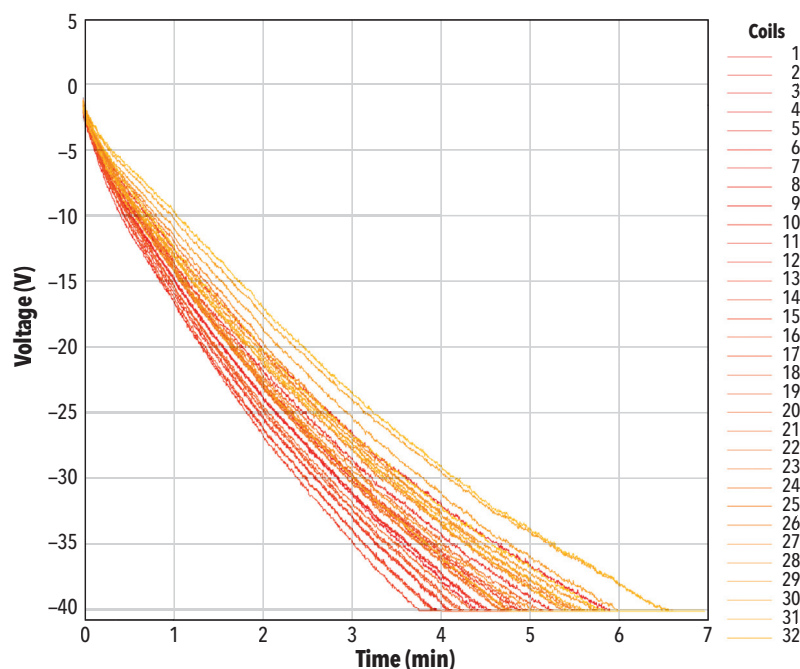
To mitigate environmental effects on the robotic ECA measurements, the system was programmed to null the array probe in the damage-free region at fixed intervals. Additionally, a second-order detrending process was applied to each coil signal in the time domain.

### Image Processing Algorithms for Corrosion Detection

To address liftoff variations and environmental effects, the post-processing workflow incorporates a specialized array subtraction algorithm and detrending. This approach leverages the shared liftoff errors across the coils to isolate and correct these inconsistencies effectively. A simplified representation of the post-processing procedure is provided in Figure 6. A detailed description can be found in the authors’ previous work (Hamilton 2024).

### Array Subtraction Algorithm

The array subtraction algorithm removes common liftoff effects across all probe channels by subtracting the mean value of the line scans, effectively eliminating identical noise and voltage variations between coils. It is applied to ECA data in the time domain to prevent spatial misalignment caused by delays



**Figure 5. Voltage fluctuations in the coils (absolute mode) caused by array probe heating during warm-up and hot air circulation around the probe.**

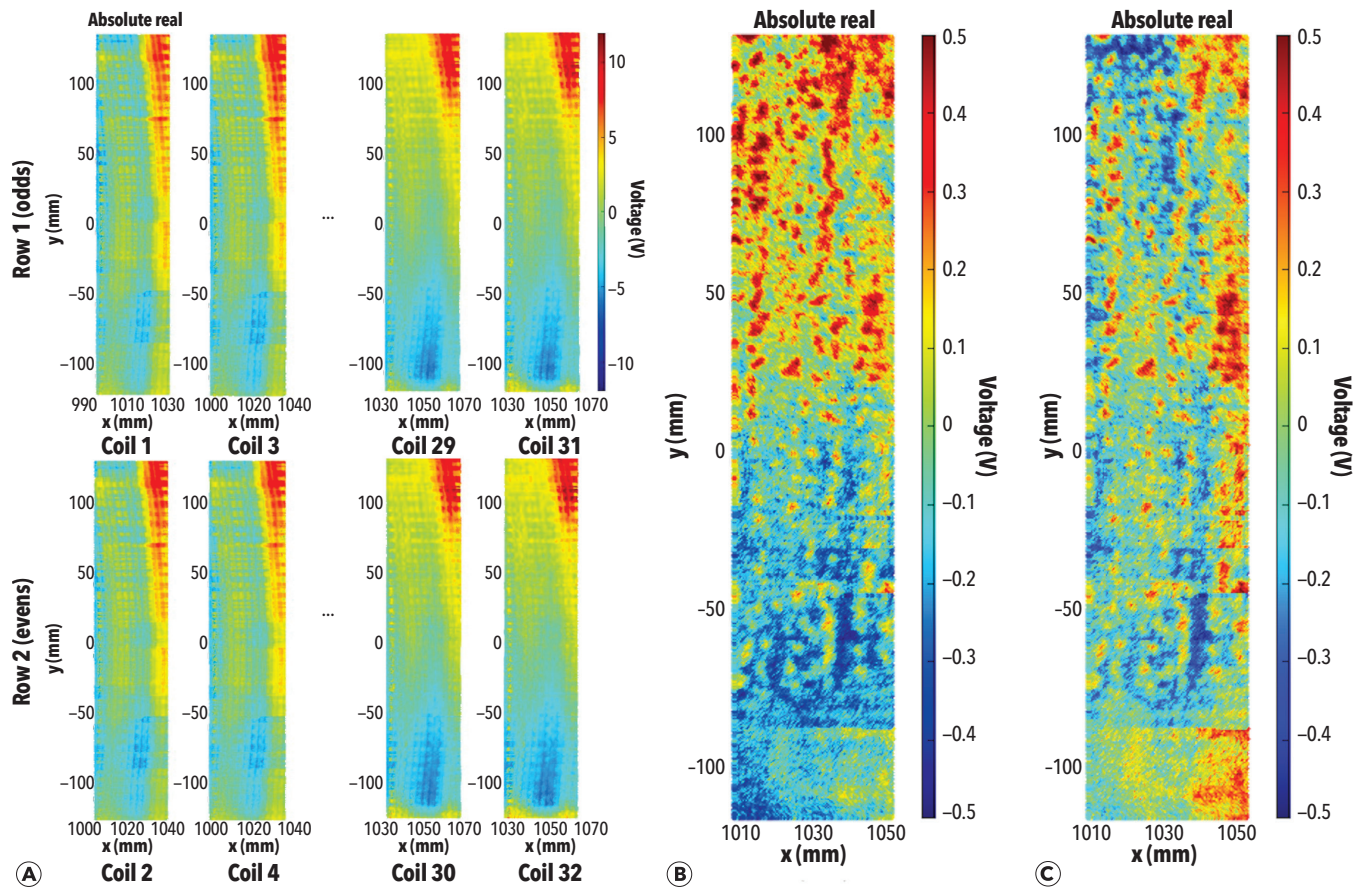


Figure 6. Post-processing of ECA image data in spatial domain: (a) raw data per each coil; (b) diagnostic image after array subtraction; (c) diagnostic image after array subtraction and detrending.

between the robot controller and the ECA data acquisition system. The process follows these steps:

1. Normalize each line scan per coil (range: 0 to 1).
2. Compute the mean voltage across all channels at each time instance.
3. Subtract the mean from the normalized voltages.
4. Convert the normalized values back to the original voltage units.

### Detrending Algorithms

In addition to array subtraction, three detrending methods are applied to the ECA data. Detrending is performed across space using the  $x$  and  $y$  coordinates, while excluding the  $z$ -axis. The underlying assumption is that robot positioning errors occur at a lower spatial frequency than corrosion damage, allowing their removal through detrending. The procedures are as follows:

1. Linear detrending for signals in the time domain.
2. Planar spatial detrending ( $1 \times 1$  order) along  $x$  and  $y$  coordinates.
3. Higher-order spatial detrending ( $3 \times 3$  order) along  $x$  and  $y$  coordinates.

### Experimental Validation of Robotic ECA System

This section presents the experimental validation of the robotic ECA system on curved steel samples with corrosion damage.

Additionally, we demonstrate the application of the proposed image processing algorithm for enhanced damage detection.

### Acquisition and Processing of ECA Measurements

This section presents the experimental ECA measurements obtained using the developed robotic setup and their comparisons with microscopic images of corroded steel samples. Figure 6 outlines the ECA data processing workflow for flat Sample A, where all voltage processing is performed along the  $x$  and  $y$  coordinates. Figure 6a displays raw measurements from individual coils, while Figure 6b illustrates the scan using the ECA probe. The array subtraction algorithm is applied to remove common coil trends from the array image data. The final processed image, shown in Figure 6c, results from detrending to eliminate liftoff and tilt variations, with the detrend magnitude detailed in Figure 4b.

Figure 7 demonstrates the effect of processing ECA data over time. In Figure 7a, voltage spikes occur as the array probe nears the sample edge due to increased liftoff. These artifacts are largely removed in Figure 7b after processing.

Figures 8 and 9 present the results for both full and fast scans after the post-processing steps described earlier. Corrosion is visible in most datasets, though some inaccuracies persist post-processing. Full scans, acquired using Coil 16 near the center of the array, exhibit tilting effects along the  $x$ -axis in

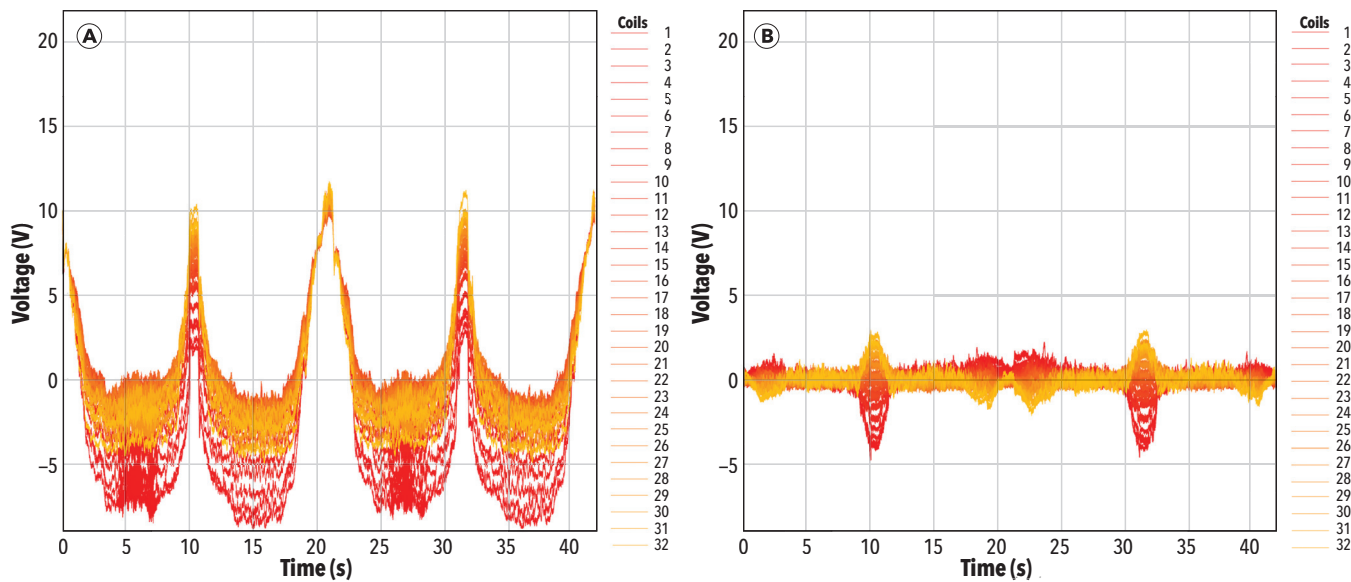


Figure 7. Post-processing of ECA line scans using array subtraction and detrending in time domain: (a) raw line scans; (b) processed line scans.

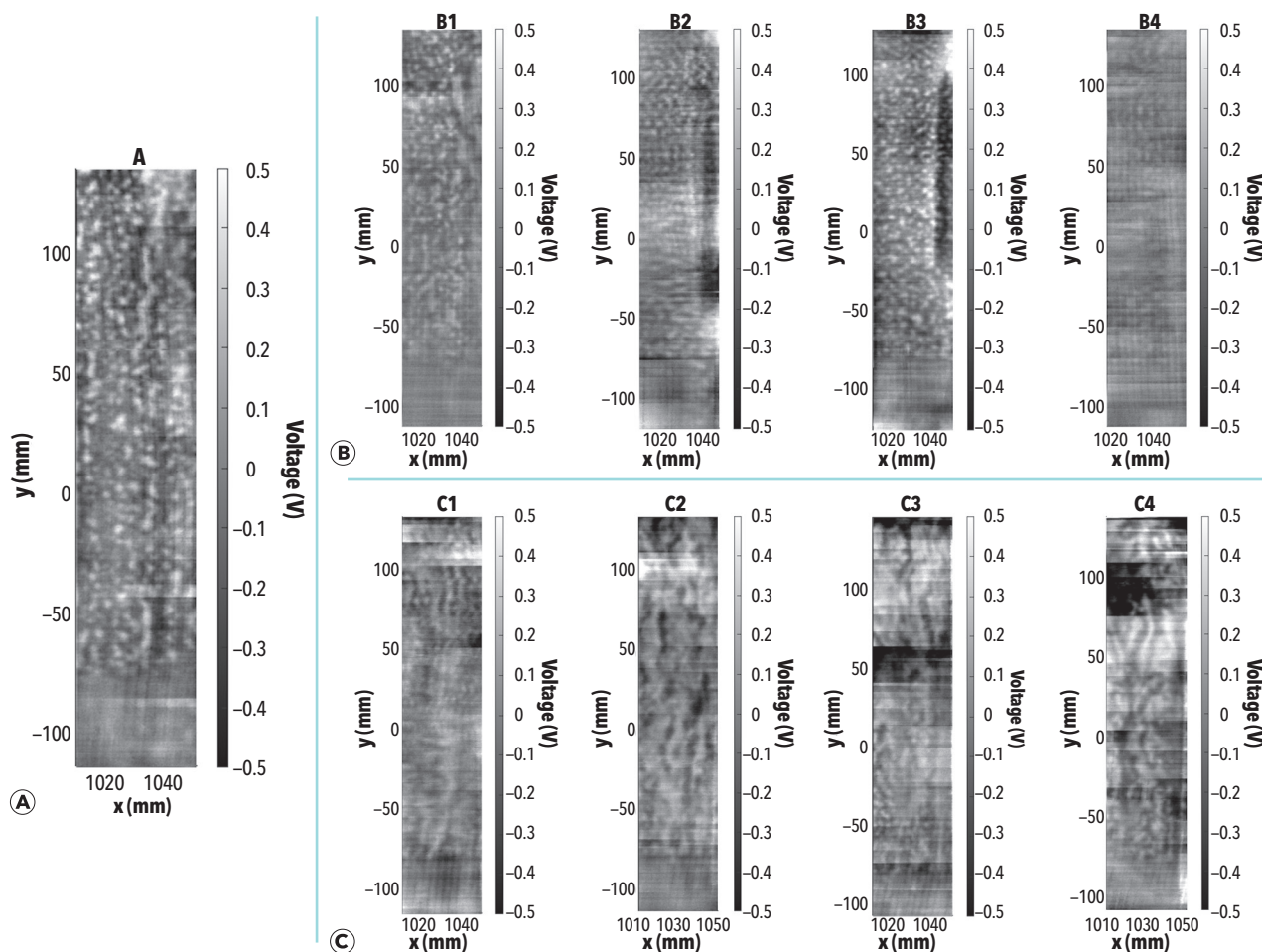


Figure 8. Full eddy current scans for steel samples: (a) flat sample A; (b) concave samples B1-B4; (c) convex samples C1-C4.

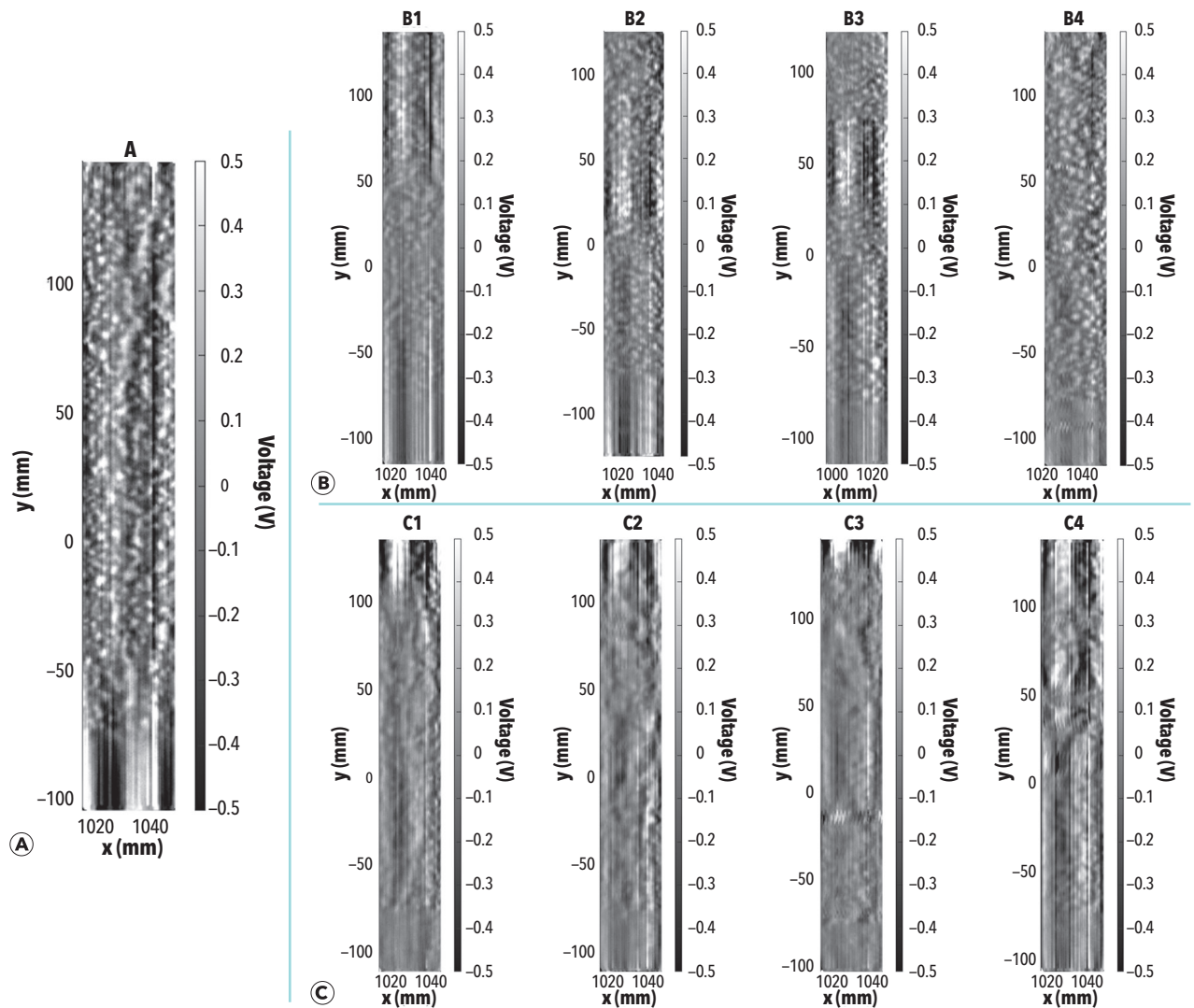


Figure 9. Fast eddy current scans for steel samples: (a) flat sample A; (b) concave samples B1–B4; (c) convex samples C1–C4.

convex sample set C. In concave sample sets B2 and B3, the right side of the scans shows saturation due to probe orientation errors, while set B4 displays desaturation across the entire scan—an issue absent in the corresponding fast scan using the same model. Fast scans experience similar tilting effects but along the y-axis.

### Comparison of ECA and Microscopic Data

The validation algorithm compares ECA scans of corroded steel samples with corresponding microscopic images of corrosion depth to assess the accuracy of the robotic NDE system. Due to the time-intensive nature of microscopic imaging and reconstruction, comparisons are performed only on randomly selected regions of the test samples (D1–D4), as shown in Figure 10a. The validation process follows these steps:

- 1. Data preprocessing.** The microscopic data (Figure 10c) is downsampled to match the pixel size of the ECA image (Figure 10b), as the ECA scan covers a significantly larger area.

- 2. Alignment via cross-correlation.** A cross-correlation analysis is performed to align the datasets. The algorithm searches within the ECA data, computes the cross-correlation, and registers the location with the highest match of image patterns, as illustrated in Figure 10d.
- 3. Defect identification.** Once aligned, an intersection operation is applied to identify defect regions. The ECA data is thresholded, classifying values greater than zero as defects (coded as “1”) and background areas as “o.” In contrast, the microscopic data is thresholded such that values below zero are marked as defects (“1”), while the background remains “o.”
- 4. Final classification.** The binary masks from both datasets are combined and averaged, as shown in Figure 10e. Defect regions detected in both datasets are assigned a defect code of “1” (white), background areas remain “o” (black), and regions with no direct overlap receive an intermediate value of “o.5” (gray). The percentage of intersection is then calculated, excluding the gray areas.

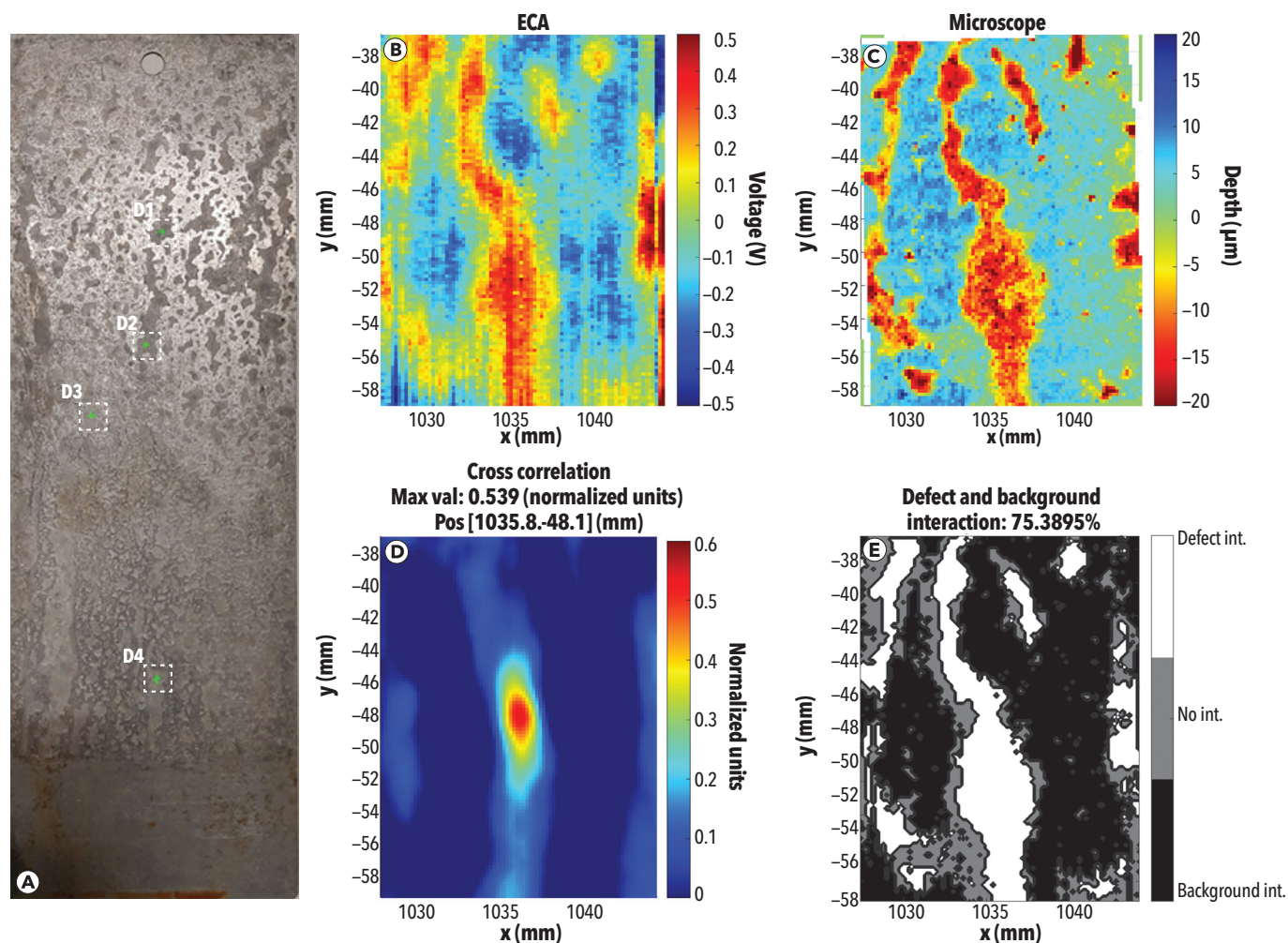


Figure 10. Experimental data for Defect D4 on corrosion Sample A: (a) locations of scanned regions D1-D4 on Sample A; (b) ECA scan of D4; (c) corrosion depth profile of D4 from the microscope; (d) the cross-correlation map between the ECA and microscopic images; (e) intersection between the ECA and microscopic images.

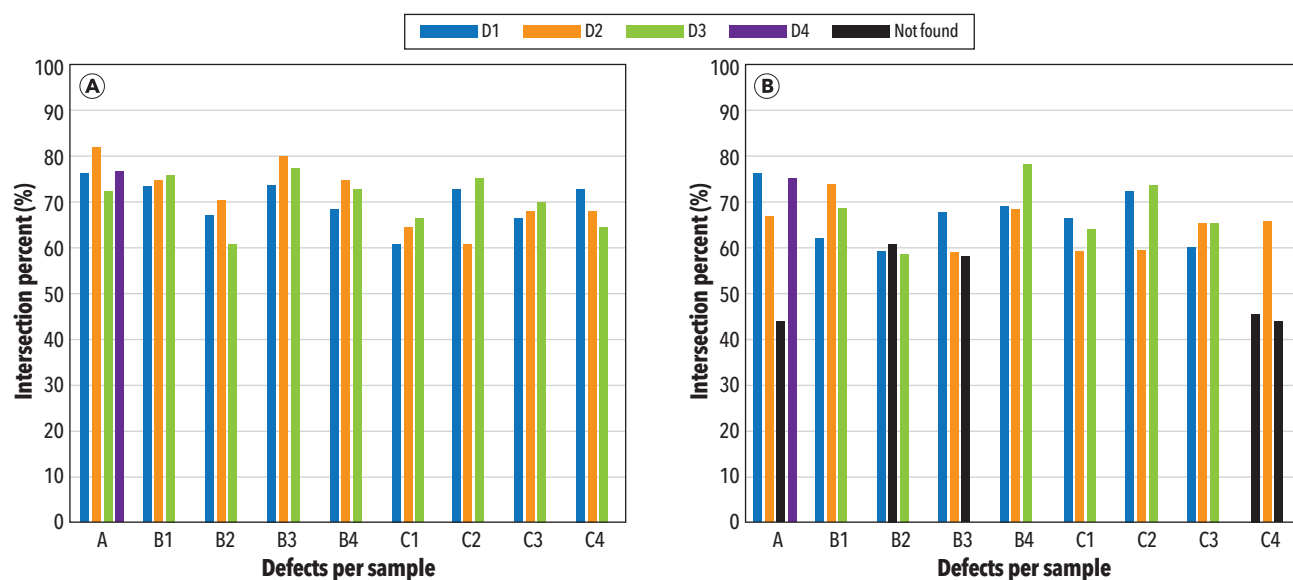


Figure 11. Intersection of the ECA and microscopic images in selected regions D1-D4 on corroded steel samples: (a) full scan results (ECA image obtained using one coil in the array); (b) fast scan results (ECA image obtained using the full array).

The gray regions in Figure 10e, indicating a lack of overlap between the ECA and microscopic datasets, result from the inherent blurriness of the ECA image compared to the high-resolution microscopic data. This blurriness occurs because the ECA sensor coils integrate magnetic field responses over their sensing area, leading to a less sharply defined defect boundary.

Figure 11 summarizes the validation of ECA results for all test samples with corrosion damage. The intersections between post-processed ECA scans and corresponding microscopic images were calculated for randomly selected regions (D1–D4) in all corroded samples, including the flat Sample A and the curved sample sets B1–B4 and C1–C4. A comparison was also made between full scans (single-coil raster scans) and fast scans (full-array, single-pass along the sample's long side).

The results showed strong agreement between ECA and microscopic images across all scans, including those on curved surfaces, highlighting the robustness of the signal processing approach used in this study. As shown in Figure 11a, full scans exhibited a high degree of intersection with microscopic data, indicating strong correlation. However, in fast scans, some randomly selected regions (D1–D4) were not effectively covered due to the single-pass nature of the scan, which followed the centerline of the sample. Consequently, for these regions, intersection evaluation was not possible. Instances where the array probe was out of bounds relative to the microscopic measurement regions are labeled as “not found” in Figures 11a and 11b.

## Conclusions and Future Work

This work presents a robotic eddy current array (ECA) system developed for detecting corrosion on curved metallic surfaces, addressing key challenges such as inconsistent probe liftoff, tilt, and environmental factors. A post-processing workflow, including array subtraction and detrending techniques, was implemented to correct these errors and improve defect detection accuracy. The system showed promising results when tested on samples with varying curvatures, correlating well with ground truth data from a digital microscope. While liftoff and tilt caused some inaccuracies, the system was able to detect corrosion defects effectively. The integration of computer vision-based path planning and precise sensor alignment were essential to optimize measurements, demonstrating the system's potential for use in complex geometries and real-world scenarios.

Future work will focus on improving the robotic ECA system by addressing liftoff variations and enhancing robot calibration. More automated and accurate surface reconstruction methods, such as iterative closest point (ICP) algorithms or AprilTags (Olson 2011), will replace the current point-pair picking method. Adaptive path planning will also be explored, enabling the robot to adjust its scanning path based on real-time ECA data, which will require further development of voltage-to-depth calibration techniques. Additionally, the system will be extended to mobile and aerial platforms,

enabling autonomous inspection of large-scale or remote structures. These improvements will support NDE 4.0's goals of increasing automation, precision, and scalability in real-world inspection scenarios.

## DATA AVAILABILITY

A detailed description of the post-processing procedure used in this study for the eddy current array image data is available from the corresponding author upon reasonable request.

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## BECOME AN ASNT ADVOCATE!

Over my more than five years at ASNT, I have noticed some significant trends within our membership. First, you are passionate about what you do, which includes the NDT field, your respective industries, and your individual jobs. NDT is clearly important to you, and you want others to appreciate how important NDT is to your nation's health and safety, as well as the quality, reliability, and performance of your companies and employers. Second, you feel that NDT is either not well-known or it is underappreciated by your clients, stockholders, senior managers, coworkers, governments, and the public. Third, if given the opportunity to share your passion for NDT or to convince others of the importance of effective NDT, you will actively engage in such activities. This is a good thing!

ASNT recently held its first Hill Day. "Hill days" are when an association's members travel to Capitol Hill in Washington, DC, to meet with Congressional members and their staffs to discuss issues important to the association. In ASNT's case, more than 50 members and staff met with Senate and House members and their staffs to educate them about NDT and two critical issues: the workforce shortage and the need for increased government funding for NDT research. The good news is that our messages were well-received—everyone we met with appreciated learning about NDT and its indispensable role in our society. The bad news is that we have our work cut out for us to get legislation introduced in the current political climate.

I would like to extend my heartfelt thanks and appreciation to our members who took the time to travel to DC and join us on that historic day. You all made a huge impact! I would also like to thank our amazing staff team, led by Director of Public Relations and Government Affairs Garra Liming, who organized and coordinated more than 150 meetings held across two days on the Hill.



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the NDT field, if  
you want the world  
to recognize and  
appreciate NDT, and  
if you are ready to  
share your passion  
and our message,  
then join ASNT's  
advocacy team  
now.**



**A group of ASNT  
members and  
staff gathered in  
Washington, DC, for  
ASNT's first Hill Day on  
11 March.**