

GUIDED BY HEARING: ROBOTIC MOTION PLANNING FOR PRECISION IN GAS LEAKAGE LOCALIZATION

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ABSTRACT

This research proposes a motion planning framework for a robot equipped with a bioinspired hearing system to enhance its sound source localization, specifically for gas leak detection. Similar to how animals use movements, such as changing positions or rotating their ears, to precisely localize a sound source, this framework enables the robot to improve its estimation of both direction and distance through strategic motion. The proposed method uses the time difference of arrival (TDOA) between two wideband optical microphones, obtained through this motion, to accurately estimate the direction and distance of a sound source. We first introduce the underlying concepts and validate the approach using experimental data collected with a collaborative robotic arm. We then demonstrate the implementation of the method on a quadruped robot. The results show that the method can be effectively deployed on mobile robots, achieving directional and distance accuracy for gas leak localization.

KEYWORDS: gas leakage, source localization, quadruped robot, robotic dog, robotic inspection

Introduction

Gas leakage is a significant source of failure in various industries, including oil and gas, clean energy systems such as hydrogen-based fuel cells, and the automotive sector. Early detection of gas leaks is crucial to prevent catastrophic failures, ensure safety, and reduce environmental impact. Gas leakage detection and localization involve using a wide range of gas sensing hardware, including metal oxide (MOX) gas sensors, e-noses, and photoionization detectors (Francis et al. 2022). Relying on human labor is demanding, while installing sensor equipment can be expensive and often financially unfeasible. As a result, there is growing interest in using mobile robots for inspection, such as Boston Dynamics' Spot (Guizzo 2019).

While the use of robots for industrial inspection is not new, the application of mobile robots for inspection remains an active research area. A review of various pipeline robots, considering factors such as inspection accuracy, adaptability, cost, and efficiency (Ambati et al. 2020), as well as the development of inspection robots for nuclear power plants (Yamamoto 1992; Fu et al. 2006), demonstrates a long-standing interest in this field. Furthermore, the use of robots has expanded into other industrial applications, including waste deposits and electric power cables (Jiang et al. 2005); civil engineering tasks like inspecting building facades and concrete structures (Ilyas et al. 2021); examining structures such as ships, wind turbines, and aircraft (Almadhoun et al. 2016); and underwater facility inspections (X. Wang et al. 2022). More recently, several systems have been proposed for surveying nuclear power plants to assess radiation levels (Abadi et al. 2023; Mitchell et al. 2023). In the context of gas source localization, Francis et al. (2022) provide an overview of gas detection principles and review existing works that propose the use of mobile inspection vehicles.

Since vertebrates became terrestrial 370 million years ago, reliable information has been essential for making survival decisions (Munoz and Blumstein 2020; Thewissen and Nummela 2008). In our paper, we draw inspiration from the remarkable evolutionary strategies employed by vertebrates in their survival and adaptation within the animal kingdom. The fundamental principle of aeroacoustics leak detection revolves around the generation and propagation of sound waves when gas escapes from a pipeline (S. Wang and Yao 2020). These acoustic signals carry crucial information about the leak, such

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as its magnitude, location, and potential impact on the pipeline's integrity (Liang et al. 2013). The main advantages of using acoustic signals for gas leak diagnosis include swift response time, long range, and precise localization (S. Wang and Yao 2020). A key drawback of using acoustic signals is their reduced sensitivity as the sensors move farther away from the source due to significant attenuation (Liu et al. 2017). This attenuation is even more pronounced with higher-frequency sounds (ultrasound), which are often involved with smaller leakages. One effective approach to mitigate this problem is by employing an array of microphones along with acoustic imaging techniques (Li et al. 2021; Fluke 2021; Drives & Controls 2021). However, this method generates a substantial amount of data, which is not ideal for a near-real-time approach required for creating a semi-autonomous platform and quick response. Fortunately, this issue has been ingeniously addressed by biological systems in their evolutionary acoustic sensing systems, using only two ears (binaural sensing). Instead of relying on increased sensor numbers to enhance sensitivity, these biological systems evolved their external ear (pinna) shapes to act as hardware for magnifying sound coming from specific directions. This evolution was further complemented by strategic motion and motion control of the pinna and head as well as their movement (Populin and Yin 1998; Fletcher 2014), allowing them to dynamically change acoustic directionality and sensitivities as needed. Inspired by these biological mechanisms, we propose in this paper an acoustic sensing system that comprises two microphones, mimicking two ears and binaural hearing, with a framework designed to optimize or strategize movement to improve source localization accuracy.

Sound source localization (SSL) is a prominent topic in robotics, with a detailed review of common methods provided by Rascon and Meza (2017). While gas and air leak localization is essential for industrial inspections and has been explored in earlier research, many existing approaches rely on fixed microphone arrays (Eret and Meskeel 2012), handheld devices (Liao et al. 2013) for manual detection, and statistical time-domain features for pinpointing leaks in pipes (F. Wang et al. 2017). Yan et al. (2018) used a four-element linear array to identify multiple sources with the MUSIC algorithm within the 63–187 kHz emission range. Focusing on ultrasonic emissions from leaks in pressurized pipes, Schenck, Daems, and Steckel (2019) employed a peak search on a beam-formed spectrum and use a 32-element microphone array. By leveraging multiple poses of the robot and integrating simultaneous localization and mapping (SLAM) techniques with the microphone array, potential leaks are effectively localized. Most recently, G. K. J. Fischer et al. (2024) introduced an autonomous robotic system for comprehensive plant inspection, equipped with a variety of sensors, including lidar, stereo, UV/IR/RGB cameras, electronic noses, and five microphones. These sensors detect factors like methane leaks, flow rates, and infrastructure issues. The system was tested at a wastewater treatment site, achieving gas leak localization with a 50 cm error through acoustic assessments.

Current robotic systems for industrial inspection rely on various sensors, such as lidar, stereo, and depth cameras, to map environments for navigation and distance estimation. However, little attention has been given to optimizing the robot's movement and positioning to enhance leak localization once an anomaly, such as sound generated by a leak, is detected by the microphones. Typically, these systems use microphone arrays to estimate the direction of arrival (DOA) of sound, combined with techniques like SLAM and lidar to locate the leak. While multi-microphone array techniques can perform well from fixed positions, they often require more complex hardware setups, increased costs, and larger physical space. In contrast, the proposed method achieves accurate localization using a simpler hardware setup (two microphones) with lower computational demands. This is accomplished by strategically leveraging the robot's mobility, effectively trading hardware complexity and computational power for movement. Specifically, this paper explores how motion, combined with a two-microphone array inspired by an animal's external auditory system, enhances sound source localization. In other words, we focus on optimizing the robot's movement strategies to acquire samples that enable precise sound source localization while maintaining a lightweight system configuration. First, we examine the effect of motion using a fixed-base collaborative robotic arm. Based on the insights gained from this study, we propose a motion strategy to enhance the robot's source localization. Finally, we implement this strategy on a quadruped robot to explore its effectiveness for mobile platforms.

Method

This section provides a comprehensive overview of our methodology, covering the sound source localization approach, acoustic data acquisition process, robotic systems, and experimental setup.

Source Localization Method

The time difference of arrival (TDOA) between two signals is commonly estimated by calculating a cross-correlation vector (CCV). The Pearson correlation factor, as shown in Equation 1, provides the simplest way of calculating the CCV (Rascon and Meza 2017):

$$(1) \quad CCV[\tau] = \frac{\sum_i (a_1[t] - \bar{a}_1)(a_2[t - \tau] - \bar{a}_2)}{\sqrt{\sum_i (a_1[t] - \bar{a}_1)^2} \sqrt{\sum_i (a_2[t - \tau] - \bar{a}_2)^2}}$$

where

- a_1 and a_2 are the two discrete signals being compared,
- τ is the time shift applied to a_2 , and
- $\bar{a}_1$ and $\bar{a}_2$ are the mean values of a_1 and a_2 , respectively.

Although computationally efficient and straightforward, CCV-based TDOA estimation is highly susceptible to environmental noise and reverberations, often leading to inaccurate estimates (Brandstein and Silverman 1997). To mitigate these challenges, the Generalized Cross-Correlation with Phase

Transform (GCC-PHAT) method has become widely preferred due to its robustness against noise and reverberation (Knapp and Carter 1976). Additionally, GCC-PHAT demonstrates resilience in high signal-to-interference ratio (SIR) environments, effectively managing interference from additional sources (Kwon et al. 2010). This characteristic aligns well with the experimental conditions in our study, where high SIR levels are preserved despite background noise from air conditioners, laboratory equipment, and the robots themselves. These factors support the selection of GCC-PHAT for TDOA estimation in our setup.

To provide a comprehensive comparison with alternative TDOA estimation algorithms, we also implemented the coherence-based method (Carter 1987) and the Smoothed Coherence Transform (SCOT) method (Carter et al. 1973). The results reveal that TDOA estimates are consistent across all methods, exhibiting a standard deviation of 1×10^{-6} relative to GCC-PHAT. However, in terms of computation time, SCOT and the coherence-based method performed slightly better, with average times of 0.050 s and 0.0519 s, respectively, compared to GCC-PHAT's 0.0685 s.

The GCC-PHAT operates in the frequency domain, as shown in Equation 2:

$$(2) \quad CCF[f] = A1[f]A2[f]^*$$

where

$A1$ and $A2$ are the Fourier transforms of a_1 and a_2 , respectively, and the $\{.\}^*$ operator denotes the complex conjugate.

By applying a weighting function $\psi[f]$, the generalized cross-correlation (GCC) is obtained, as shown in Equation 3:

$$(3) \quad GCCF[f] = \psi[f]A1[f]A2[f]^*$$

The phase transform (PHAT) weighting, given in Equation 4, normalizes the magnitude of the cross-spectrum, preserving phase information and enhancing robustness to amplitude variations:

$$(4) \quad \psi[f] = \frac{1}{|A1[f]A2[f]|}$$

Finally, the GCC-PHAT function is expressed as:

$$(5) \quad PHAT_F[f] = \frac{A1[f]A2[f]^*}{|A1[f]A2[f]|}$$

TDOA is computed by taking an argmax over $PHAT_F$. Once the TDOA is calculated, it can be used to determine the distance of the sound source from the microphones:

$$(6) \quad \Delta d = c * \Delta t$$

$$(7) \quad \Delta d = \sqrt{(x_2 - x)^2 + (y_2 - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2}$$

where

c is the speed of sound (set to 343 m/s for this study), Δt denotes TDOA, and the coordinates (x_1, y_1) and (x_2, y_2) represent the known positions of the microphones, forming a hyperbola.

In two dimensions, sound source localization (SSL) can be achieved by calculating two or more hyperbolas and identifying their intersections, as indicated in Figure 1. To determine these intersections, we apply the nonlinear least-squares method to solve the resulting system of equations (Coleman and Li 1996; Levenberg 1944).

In this study, we focused on two-dimensional source localization for the following reasons: (1) Simplifying the problem to better understand path planning strategies that can improve source localization accuracy, (2) Assuming the source is approximately at the same level as the moving platform, (3) The source was considered far enough that the Z-dimension was less significant compared to the X and Y dimensions, and (4) The platform's motion was limited, and we did not account for sensor rotation around the X or Y axes.

Acoustical Data Acquisition

Gas leaks typically produce acoustic frequencies ranging from 10 kHz to 100 kHz, with the most pronounced energy difference between leak signals and ambient noise occurring around 40 kHz. This makes 40 kHz an ideal frequency for gas leak detection due to its clear distinction from background noise. For this study, directional optical microphones were used due to their broad detection range (10 Hz to 1 MHz) and low self-noise (B. Fischer 2016; Delic 2019).

Data was collected using a NI data acquisition system, capable of sampling up to 20 MS/s per channel. To meet the Nyquist theorem requirements for 40 kHz detection, the system used a sampling rate of up to 400 kHz, ensuring accurate signal representation. To simulate a gas leak, compressed air was released through an open valve.

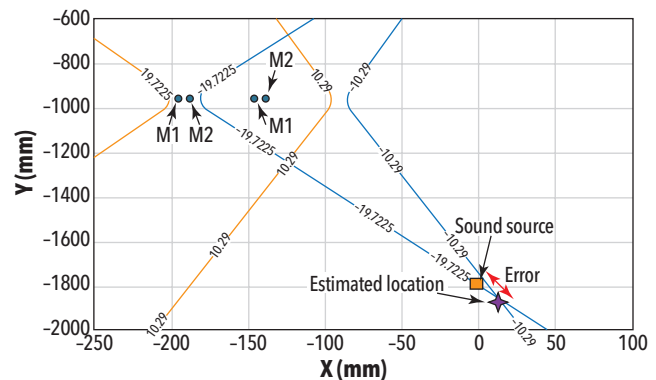


Figure 1. Sound source localization (SSL) using formed hyperbolas.

Robotic System

To explore the impact of dynamic motion on gas leakage source localization, two robotic systems equipped with microphones were used: a fixed-based robotic arm and a quadruped robot (robotic dog). The robotic arm, a collaborative robotic arm developed by Universal Robots and known for its precision and repeatability (± 0.03 mm), was used to study the effects of translational and rotational microphone motions while the sound source remained fixed. Its high accuracy supports the development of localization algorithms by minimizing estimation errors. However, its fixed-base design and 850 mm reach limit its applicability in industrial settings.

In contrast, the robotic dog, a quadrupedal robotic platform, is more suitable for deployment in industrial settings. This robotic dog is equipped with a 16-channel lidar and a depth camera. It can map the environment, detect pipelines with potential gas leakage, and generate depth maps for precise localization. Its ability to navigate varying terrains enables broader coverage for gas leak detection. It can also be enhanced with biomimetic pinnae-like structures, mimicking feline ear movements (yaw, pitch, roll, and independent motion) to improve sound localization by capturing multiple acoustic samples in complex settings. This enhancement presents an intriguing direction for future work, as the findings of Ruhland et al. (2015) suggest that the coordinated movements of a cat's head and pinna enable the collection of multiple acoustic samples to improve sound localization accuracy. This also introduces the possibility of fully emulating animal head and ear movements for enhanced sound source localization. Although we attempted to incorporate feline pinnae and head movements into our system, the inconsistency and unreliability of the data, compared to findings from Young et al. (1996), prevented us from achieving the desired results.

For the initial study, the microphones were mounted on a custom plate attached to the robotic arm, as shown in Figure 2a. Positioned 90 mm apart on a circular disc, they mimic the locations of feline pinnae. A similar mounting

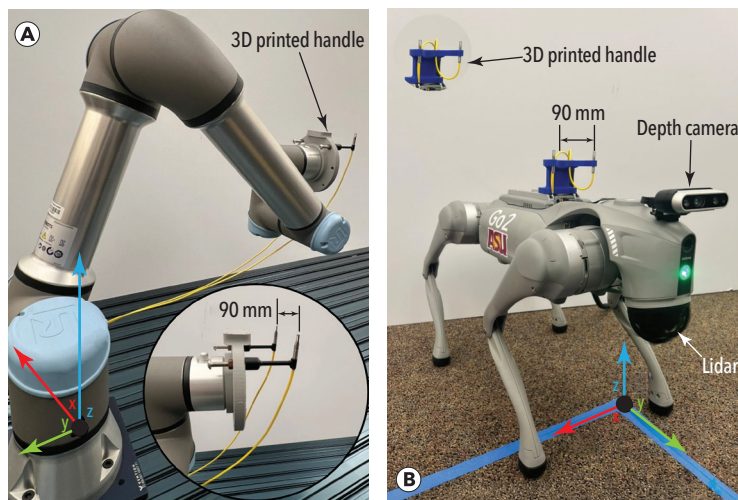


Figure 2. Microphone attachments to (a) the robotic arm and (b) the robotic dog.

bracket was created to hold and position the two microphones on the back of the robotic dog, as depicted in Figure 2b.

Experimental Setup

Biological creatures like cats and dogs rotate their heads or move their bodies to localize sound sources and enhance the TDOA of sound waves at their ears. These movements improve auditory cues that the brain uses to determine the direction and distance of a sound. When a sound originates from one side, it reaches the nearer ear slightly earlier than the farther ear. This small difference in time, known as the interaural time difference (ITD), helps the brain determine the direction of the sound source. By moving their heads or bodies, these creatures change the relative position of their ears to the sound source, creating different TDOA patterns that provide additional spatial cues for more accurate localization.

To replicate these complex motions in a simplified manner, they are divided into linear and rotational components. For linear movements, microphones were mounted on the robotic arm's end-effector. The arm followed a linear path using a linear path planner (MoveL), traversing an 8×8 grid with 50 mm increments along the X and Y axes. This systematic movement covered the designated area for sound localization experiments, with the sound source positioned 1.79 m from the robotic arm's base along the Y-axis, as shown in Figure 3a.

Rotational movements were also replicated in a separate experiment to mimic the head-turning behavior of biological creatures during sound localization. Microphones mounted on the robotic arm's end-effector were rotated along the Z-axis from 10° to 170° in 5° increments, as shown in Figure 3b. This systematic variation in microphone orientation was designed to evaluate how angular positioning affects the TDOA and enhances the accuracy of determining the direction of arrival (DOA) of sound.

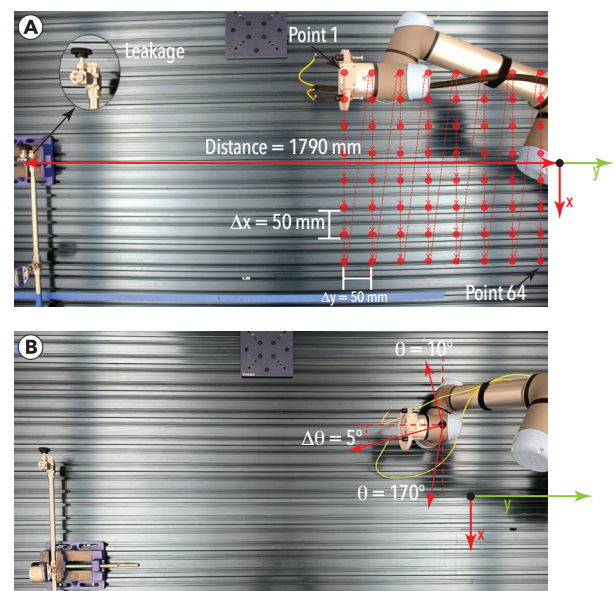


Figure 3. Movement of robotic arm: (a) linear along the X and Y axes; (b) rotational around the Z-axis.

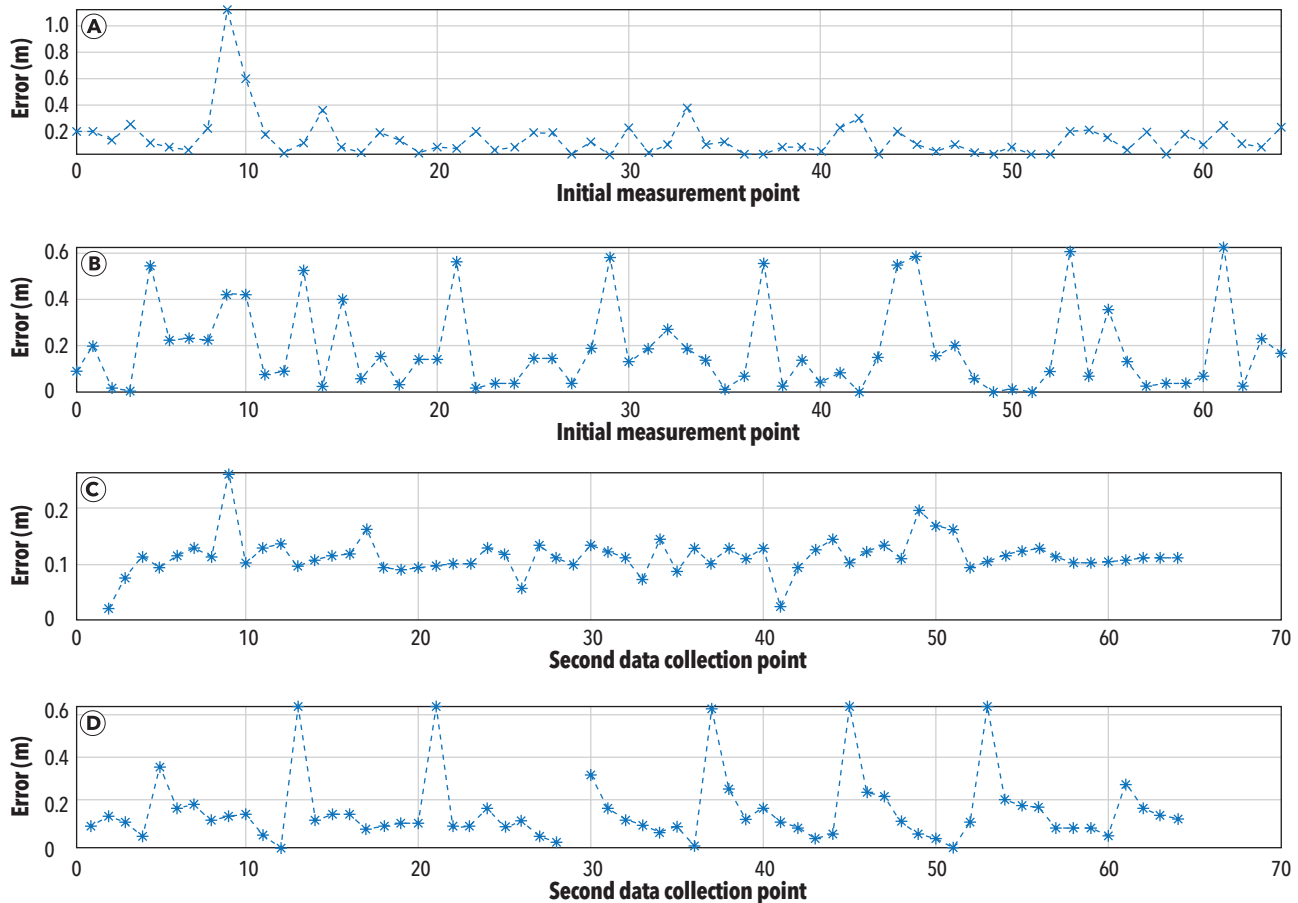


Figure 4. Minimum achievable error for each point in combination with subsequent points: (a) error in distance estimation; (b) error in direction estimation. Error distribution in leak distance estimation: Analysis based on fixing the first measurement point and its combinations with subsequent points: (c) Point 1; (d) Point 29.

Results and Discussion

The results indicate that using only two TDOAs, obtained by positioning the robotic arm at two points on the grid, the leakage direction and distance can be estimated with an error of less than 1° and 40 mm, respectively. Figure 4 illustrates the minimum achievable error when each grid point is paired with other points. One can clearly notice that not all combinations result in 40 mm distance accuracy, highlighting the importance of systematically selecting the second point for the second TDOA for distance estimation. Figure 4 explores this concept further by examining the combinations when points 1 and 29 are used as the initial measurement points. While most combinations yield good accuracy, there are certain points that the robot should avoid as the second measurement location to maintain high accuracy. Figure 5 provides color maps of the grid, where the white square indicates the first measurement point, representing the robot's initial position. By accessing the error distribution for each grid point, the robot can strategically choose the second measurement point to minimize estimation error.

Analysis of Figure 5 reveals that, in most cases, moving vertically is not a wise choice, and horizontal movement is generally more effective. This is because vertical movement often fails to provide additional information for solving the hyperbolic equations due to insufficient change of TDOA, as indicated in Figures 5c and 5d. This leads to substantial errors in source localization, as the two resulting hyperbolas tend to be nearly parallel, reducing the accuracy of the estimation.

Access to maps like those in Figure 5 can significantly aid the agent in decision-making to obtain the second TDOA. However, in real-world scenarios or with larger grids, constructing these maps and providing the agent with access becomes challenging. Therefore, we explored the range of errors the agent might encounter if it selects points randomly. As discussed earlier, relying on only two points on the grid and choosing the second location randomly is not an effective solution. Generally, increasing the number of points improves source localization accuracy. The key question is how many points the agent should randomly select to achieve reliable accuracy. To investigate this, for each fixed first location, we randomly selected two additional points 100

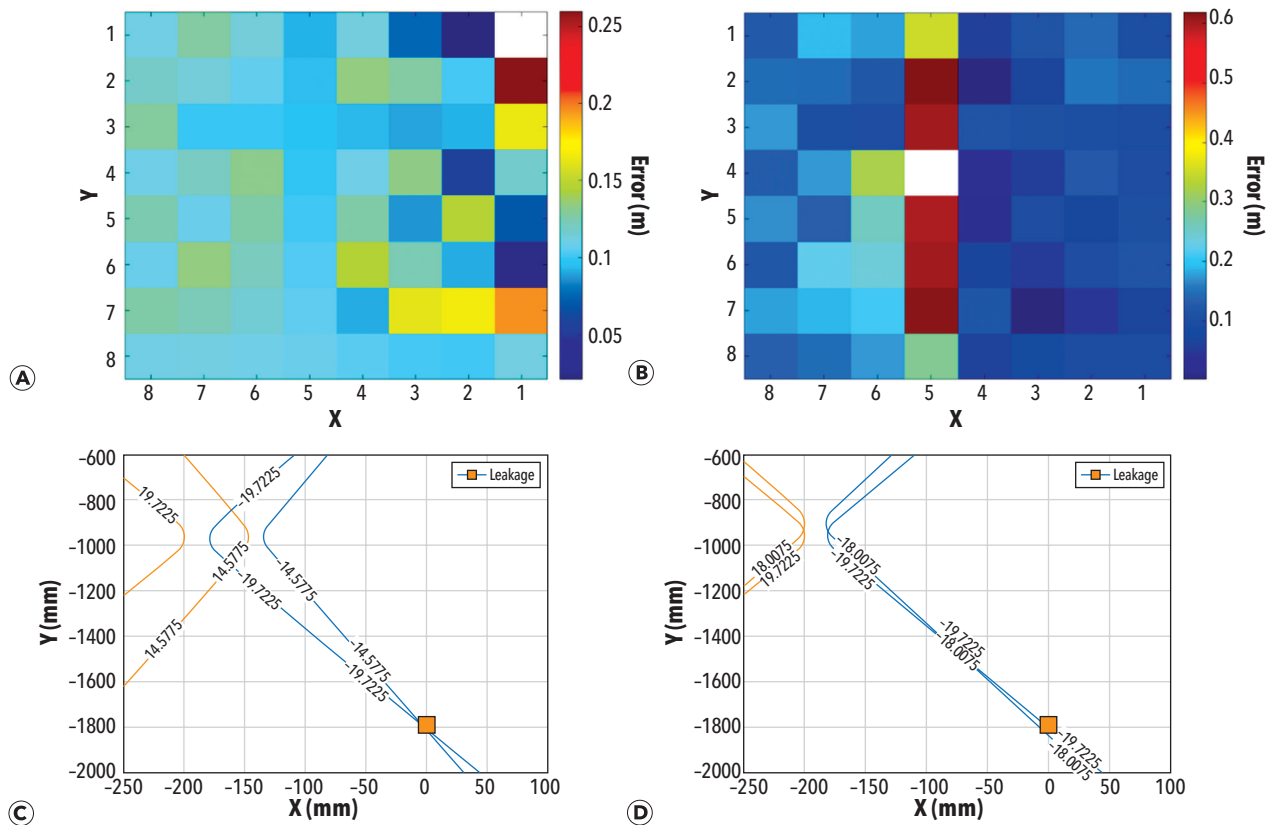


Figure 5. Distribution of error in the grid with the first location at (a) Point 1 and (b) Point 29. Intersection of hyperbolas constituted from points (c) 1 and 2, and (d) 1 and 9.

times, estimated the source location, and averaged the error in distance over these 100 trials. This approach provides a solid foundation for understanding the expected error range when the agent has data from only three locations. The same methodology was applied for scenarios with six, eight, and ten randomly chosen locations. Figure 6 illustrates the expected error an agent might encounter when starting from different grid points and selecting subsequent points at random.

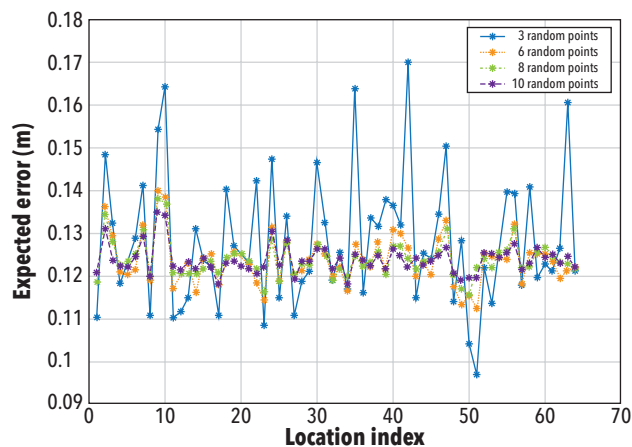


Figure 6. Expected error when the first position is fixed, and subsequent points are chosen randomly.

The expected error is significantly higher in some cases, primarily due to the agent's potential vertical movement, which increases the error. Although the expected error range becomes narrower when the number of points is increased to 10, the robot still expects a 120 mm to 140 mm error in distance.

An alternative approach involves providing the agent with additional information to enable more strategic motion planning. This additional information is obtained by rotating the microphone about the Z-axis. Figure 7 illustrates how the TDOA and amplitude change as the microphones rotate. As expected, the TDOA reaches zero when the robot is oriented directly toward the sound source (leakage). While one may expect to receive the maximum amplitude once the microphones are directed toward the leakage source, our analysis shows that the maximum amplitude slightly deviated from that direction, as depicted in Figure 7b. Consequently, starting from an initial position, the robot can rotate about the Z-axis to accurately determine the direction of the sound source (leakage) when the TDOA reaches zero. Once the direction is established, and knowing that horizontal movement is more effective, the robot can then move laterally to capture a second TDOA reading and localize the sound location. This movement strategy is tested using our robotic dog platform to replicate more realistic scenarios.

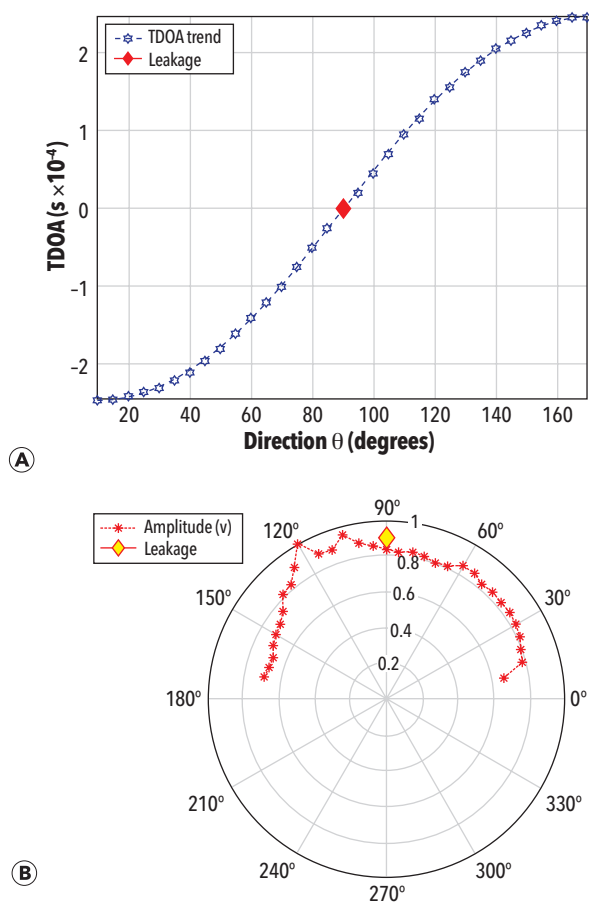


Figure 7. Angle using robotic arm versus (a) variation of time difference of arrival (TDOA) and (b) amplitude variation.

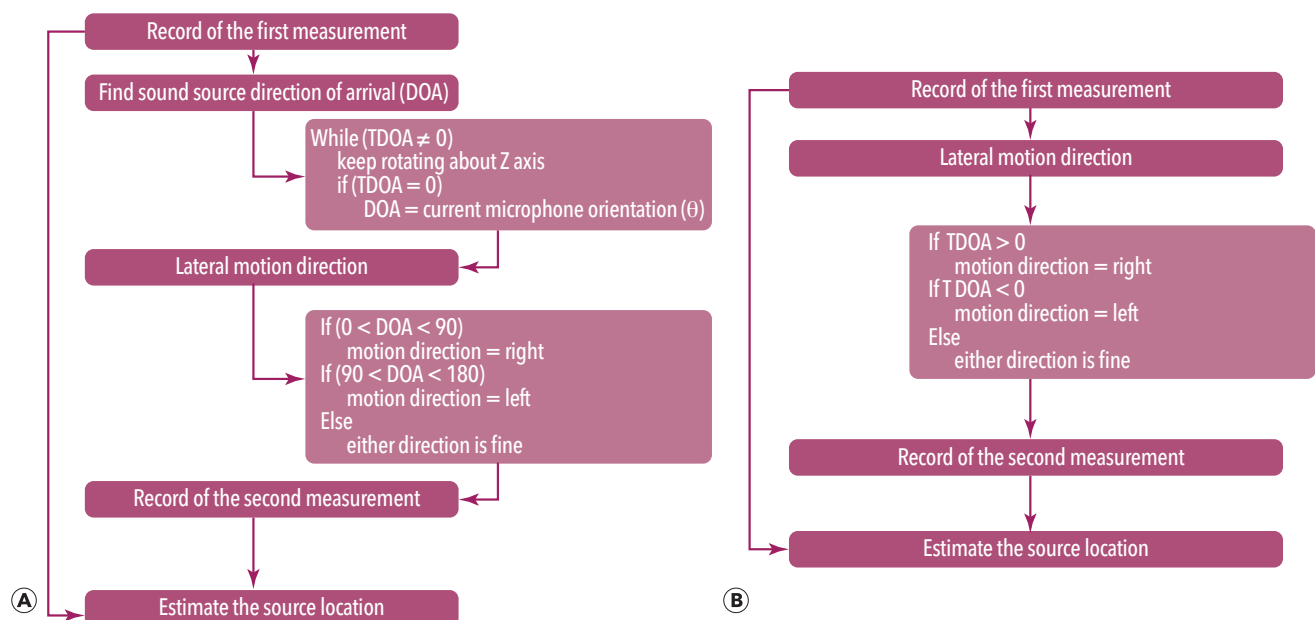


Figure 8. (a) Proposed path planning algorithm and (b) updated path planning algorithm for the robotic dog.

To integrate the source localization with this movement strategy for a mobile platform, microphones were positioned on top of the robotic dog, as shown in Figure 2b. The path planning strategy is shown in Figure 8a. Initially, the robotic dog records the first measurement at the starting point. Next, it performs a sweep of the environment by rotating around a fixed point in 15° increments to identify the direction of the source. Following this, the robotic dog moves horizontally toward the estimated source, either to the left or right. At the new position, a second data point is collected, and the source location is estimated. It is important to note that we assume the source is always in front of the robot.

To assess the effectiveness of this strategy, we conducted two experiments. In the first experiment, the robot took an initial sample at a starting point and then collected two additional samples at random locations within a grid, maintaining a consistent orientation throughout. Using the gathered data, the hyperbolic equation (Equation 7) was solved to estimate the source location.

In the second experiment, the robot first captured an initial sample and then began rotating to gather data. When the TDOA reached zero, the robot identified the source direction. With the initial sample and direction established, the robot moved horizontally to a new position to obtain a second TDOA for source location estimation. It's important to note that the robot maintained the same orientation when taking the second TDOA as it did for the first, as shown in Figure 9. Additionally, the robotic dog's rotational and translational movements were executed manually rather than autonomously, with the minimum step size for rotation being 15°. Figure 9 shows the robotic dog's motion trajectory for random and strategic walking.

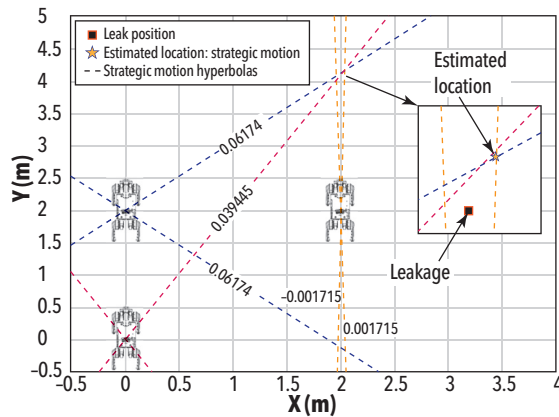
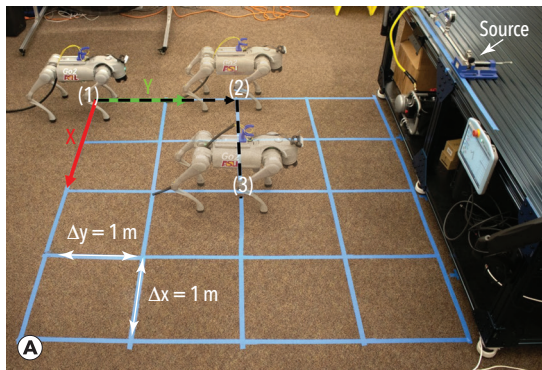


Figure 9. (a) Random walk trajectory and (b) strategic motion trajectory of the robotic dog.

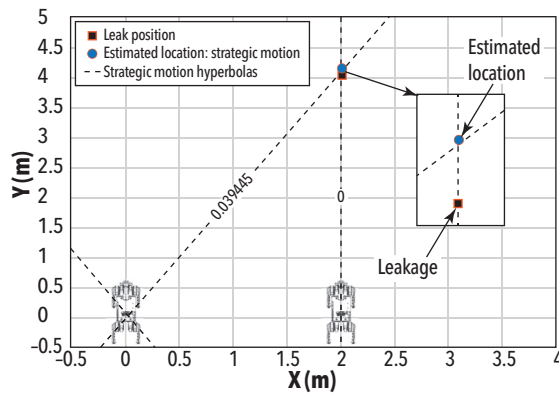
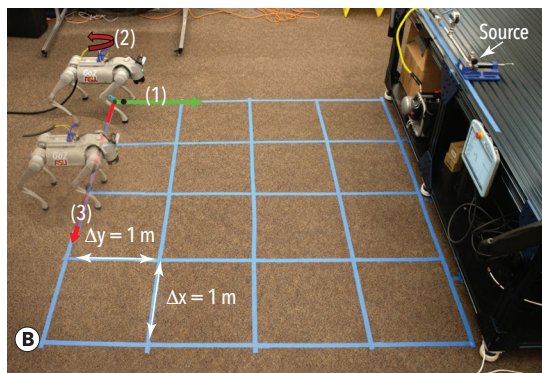


Figure 10 illustrates how the TDOA changes as the robotic dog rotates about the Z-axis from 0° to 180° , taking measurements every 15° . The expected angle for the TDOA to reach zero is 63.4° , but the results show that this occurs around 80° , with an approximate error of 15° . The authors attribute this discrepancy to several factors. Firstly, the robotic dog may not rotate exactly 15° each time, and secondly, unlike the robotic arm, the dog's axis of rotation is not fixed. As the dog rotates, it tends to shift slightly, leading to changes in its position. Therefore, the maximum obtainable resolution of 15° , combined with the rotation inaccuracies and the inability

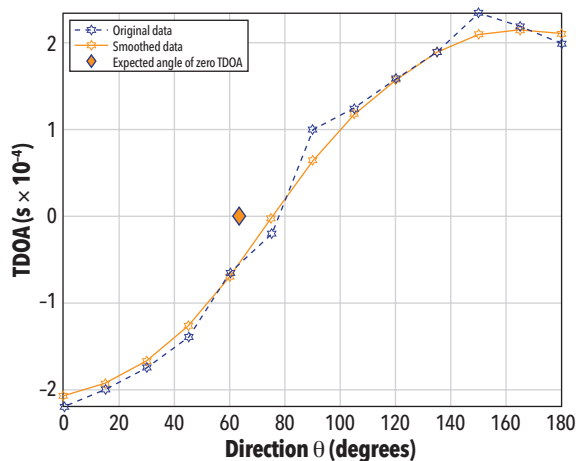


Figure 10. TDOA variation as the robotic dog rotates from 0° to 180° .

to maintain a consistent position while rotating, results in the non-smooth behavior observed in Figure 10.

Despite the imperfect direction, the information still aids the robot in selecting the next location to obtain the second TDOA necessary for localization. With the understanding that horizontal movement is more effective, the robot correctly decides to move right rather than left to capture the second TDOA. Figure 9 compares the localization results between random walking and the proposed method.

When moving randomly and taking three measurements, the error in distance is around 17 cm, which aligns with our expectation based on the expected error when the robot takes three random positions. In contrast, the strategic movement reduces this error to ~11 cm.

While the algorithm presented in Figure 8a is functional, a closer analysis reveals that the robot does not need to rotate about the Z-axis in its initial position to determine the next location. Assuming the sound source is in front of the robot, the sign of the TDOA (positive or negative) can directly guide the robot's lateral motion. Specifically, a positive TDOA indicates the robot should move to the right, while a negative TDOA suggests moving to the left. This update simplifies the algorithm by removing the need for rotational steps, thereby reducing uncertainties related to microphone positions, robot rotation angles, and the resolution of rotation step sizes. The simplified and more efficient algorithm is presented in Figure 8b.

While the results demonstrate promising applications for mobile robots, including robotic dogs, several issues need to

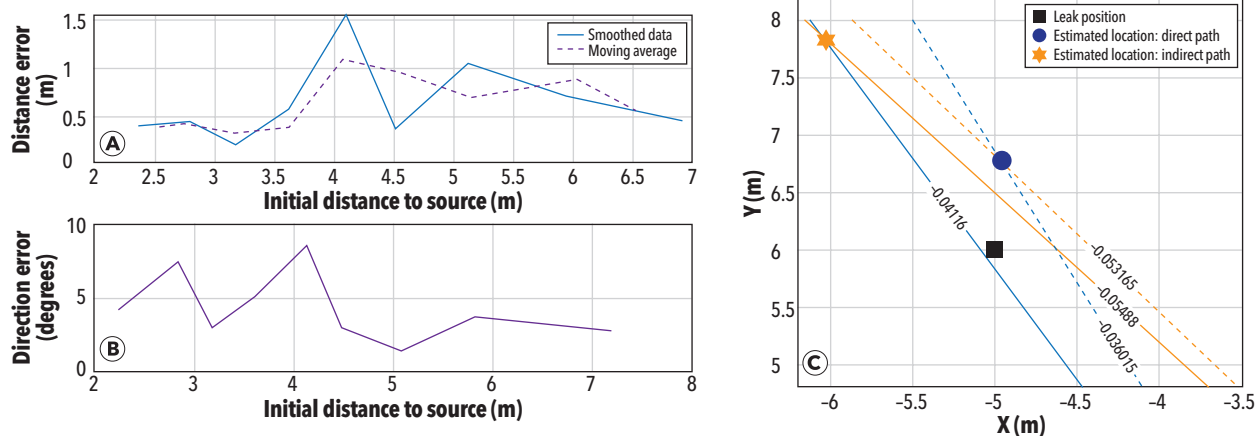


Figure 11. Sensitivity analysis on (a) distance and (b) direction; (c) comparison of localization accuracy between direct and indirect paths.

be addressed in future work. First, the assumption that the source is always in front of the robot may not hold in all scenarios. To enable the robot to discern whether the leak source is in front or behind, additional features like sound pressure levels could be beneficial. In this context, the use of pinnae or external ears may help the robot improve its sense of directionality. Moreover, to minimize noise interference and manage file sizes, the system avoids continuous recording while the robot is moving. Instead, the robot pauses briefly—less than 1 s—at each step to capture a signal. This approach ensures accurate data acquisition without the complexity of segmenting continuous recordings and mapping them to corresponding microphone positions. Furthermore, our sensitivity analysis on distance, as shown in Figure 11a, reveals that the distance estimation error generally increases as the distance to the source grows. However, as shown in Figure 11b, the direction estimation error remains relatively low compared to the distance error, aligning with the results mentioned by Rascon and Meza (2017). These findings suggest that an iterative implementation of the algorithm may be particularly beneficial in scenarios where the source is far from the robot. Additionally, iterative updates could prove advantageous in situations where the direct path to the source is blocked, forcing the robot to rely on signals arriving via indirect paths. Figure 11c illustrates such a scenario, comparing localization accuracy between direct and indirect path conditions.

On the other hand, the presence of other relatively strong sound sources may interfere with the system's performance and potentially cause confusion. While our laboratory experiment with two interfering sources—having voltage root-mean-square (RMS) ratios of 0.9 and 1.3 relative to the source at 8 m—showed no significant increase in error, the system's performance may still be affected in more complex real-world scenarios. These scenarios highlight the importance of incorporating additional features to not only determine whether the source is in front of or behind the robot, but also to guide the robot to an optimal distance from the leak for accurate

localization. Moreover, the robot should be capable of distinguishing between different sound signals, allowing it to differentiate between leakage sounds and other noise sources while moving in industrial environments. This can be implemented using supervised learning models trained on datasets such as MIMII (Purohit et al. 2019).

Future work should prioritize fully automating the processes involved in gas leak detection, including decision-making capabilities, and integrating the Z-dimension into the algorithm. This includes enhancing the robotic system to discern whether a sound source is in front or behind the robot and enabling differentiation between leakage sources and environmental noise. These improvements are crucial for autonomous navigation in industrial environments and accurate leak detection.

Environmental factors such as temperature, humidity, and obstacles significantly affect gas leak localization, emphasizing the need for robust methodologies to maintain precision (Ye et al. 2020; Zheng et al. 2021). Advanced techniques like Gaussian plume diffusion and beamforming algorithms are used to mitigate noise and adapt to varying conditions, while sensor fusion methods, such as Kalman filters and machine learning, integrate data from multiple sources to enhance reliability (Doshmanziari et al. 2020; Zhao et al. 2021). Incorporating thermal and visual data further boosts adaptability, as demonstrated by deep learning models like VideoGasNet (Zhang et al. 2022). Furthermore, real-time algorithms, such as particle swarm optimization and variational Bayesian inference, dynamically respond to environmental changes, making them indispensable for achieving precise and robust leak detection in complex scenarios (Zhang 2022; Ma et al. 2020).

Conclusion

In this study, inspired by nature, we explored the impact of rotational and translational motion on improving sound source localization (SSL) using only two microphones. Initially, we utilized the precision of the robotic arm to analyze how these

motions affect SSL estimation. Based on the insights gained, we developed a motion planning algorithm for mobile robots that optimizes movement to improve SSL accuracy. This approach was then implemented on a robotic dog to assess its effectiveness in real-world mobile robot applications. The results demonstrate that, by combining just two microphones with the proposed motion planning framework, the robot significantly improves its SSL estimation.

Future work will aim to fully automate the gas leak detection framework within the robotic system. This includes enhancing its ability to determine whether a sound source is positioned in front of or behind the robot and enabling the distinction between leakage sources and environmental noise. Additionally, the integration of multiple sensing modalities will be prioritized to improve gas leakage source localization, ensuring reliability even under varying environmental conditions.

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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 μm deep and ranging from 1 to 10 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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