Acoustic Emission Tomography for Damage Visualization in Homogeneous Material Surface Using Iterative Reconstruction Algorithm

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Abstract

Acoustic Emission Tomography (AET) is an advanced non-destructive evaluation (NDE) technique that enables subsurface defect detection by analyzing acoustic wave propagation characteristics. This study presents an application of AET for damage visualization in an aluminum specimen using an Iterative Reconstruction Algorithm (IRA). A single acoustic emission (AE) transducer was utilized with 16 linear projections at different angles, employing a dedicated R15 receiver and a transmitter transducer for data acquisition. The investigation was conducted on both an undamaged aluminum surface and an aluminum specimen with an induced circular defect to compare the slowness distribution. The artificially generated signals collected from multiple projection angles were processed to determine the time-of arrival (TOA) variations, which served as the primary input for reconstructing slowness distribution maps. The tomographic reconstruction results demonstrated a uniform slowness distribution in the undamaged aluminum sample, whereas the damaged region exhibited localized increases in slowness, effectively highlighting the internal defect. The ability of AET to visualize subsurface damage through variations in wave propagation characteristics underscores its effectiveness as a diagnostic tool for material integrity assessment. Findings in the research successfully achieved the presence of damage in the material surface which have been shown by changing the slowness mapping. The results highlight the potential of AET for applications in aerospace, automotive, and industrial manufacturing sectors, where real-time structural health monitoring (SHM) and defect detection are critical for ensuring safety and reliability.

Contribution of the Paper: Results indicate the advancement of Tomography for damage detection and visualization in materials using Acoustic signals with integrating an IRA to enhance defect visualization accuracy.

Keywords: acoustic emission tomography, iterative reconstruction algorithm, slowness distribution map, structural health monitoring, non-destructive evaluation

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1. INTRODUCTION

Ensuring structural integrity is crucial in engineering applications to prevent catastrophic failures and enhance the longevity of materials. NDE techniques play a vital role in identifying internal defects without compromising the mechanical properties of the material. Among various NDE methods, AET has emerged as a promising technique for detecting and visualizing defects by analyzing emitted stress waves. When materials experience external influ-

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ences like mechanical loads, temperature fluctuations, or pressure variations, they undergo a rapid redistribution of internal stress, generating transient elastic waves [1]. These stress waves propagate in the material and are detected by AE receiver transducers mounted on the surface. AET allows for reconstruction of interior structural flaws based on processing of the TOA of received signals, giving important information on material integrity. In spite of its benefits, precise imaging and reconstruction of internal defects by AET is still difficult, especially in homogeneous metallic materials where acoustic attenuation, sensor coupling, and wave dispersion are the prevailing factors that affect propagation behavior. Traditional AE analysis methods mostly depend on TOA-based localization methods, which presume homogeneous wave velocities and isotropic propagation directions. Real conditions, nevertheless, present complexities that restrict the precision of such kinds of methods. To overcome these difficulties, AET combines travel-time tomography with traditional TOA-based methods to create spatial slowness (inverse velocity) maps of wave propagation for an improved defect visualization method. Research in this paper aims at the application of AET for visualization of internal defects in aluminum specimens using an IRA for improving slowness distribution mapping and improving imaging quality

1.1. Background and Motivation

Structural health monitoring is essential in industries such as aerospace, civil infrastructure, and manufacturing, where early detection of defects can prevent material degradation and failure. AE-based NDE techniques have been widely adopted for real-time monitoring due to their ability to detect microstructural changes, such as crack initiation and propagation, under operational conditions [2]. Traditional AE localization methods depend on TOA differences among multiple sensors, which work well for simple structures but fail

to provide accurate defect visualization in complex metallic systems due to variations in material thickness, wave attenuation, and anisotropic propagation. To improve AE-based defect characterization, researchers have explored tomographic imaging techniques that analyze multiple wave paths to reconstruct internal wave velocity distributions. Travel-time tomography, commonly used in seismic studies and medical imaging, has demonstrated the ability to accurately model internal structures by reconstructing spatial slowness variations of wave propagation [3]. When applied to AE testing, tomography enhances defect visualization by overcoming the limitations of conventional TOA-based methods, allowing for a more detailed assessment of internal damage. However, existing research has primarily focused on composite, with limited studies exploring the effectiveness of AET in homogeneous metallic structures. In this article, we seek to fill this void by applying an IRA-based AET strategy for effectively identifying internal defects in homogeneous samples. Limited ray coverages have been used in this approach instead of a large numbers, which reduces the computational complexity.

1.2. Related work

Tomographic imaging has been extensively applied in NDE for imaging the internal structure of materials. X-ray and computed tomography (CT) are standard techniques in laboratory settings, where high-resolution imaging is used to assess structural components and determine crack formations [4]. In the same manner, seismic tomography yields subsurface imaging through inversion of body wave travel times over numerous paths, allowing the reconstruction of internal velocity distributions [5]. Current AET advances have focused on the improvement of defect localization accuracy through the application of machine learning, advanced signal processing, and iterative reconstruction algorithms. AET employs travel-time tomography principles for reconstructing slowness distributions from AE event data to allow improved internal defect imaging in materials. Studies have demonstrated its applicability in composite materials, where wave speed variations along different fiber orientations significantly affect propagation behavior. However, in homogeneous metallic structures, AE wave propagation is more uniform, requiring high-resolution imaging techniques to accurately identify internal defects [6]. IRA-based reconstruction has shown promising results in computed tomography applications by refining underdetermined inverse problems, leading to improved defect visualization and computational efficiency [7]. This research applies an IRA-based reconstruction approach to AET for enhancing defect detection capabilities in homogeneous aluminum specimens. The paper is structured as follows: Section II discusses the measurement algorithm, Section III presents the experimental setup and methodology, Section IV explained the TOA calculation methods. Finally, experimental results, discussions, and conclusions are presented in subsequent sections, highlighting the practical implications of the proposed approach.

2. MEASUREMENT ALGORITHM AND FORMULAS

In the measurement algorithm, the AET process is implemented simultaneously with AE source localization. The time of arrival (TOA) of the waves at the receiver is a function of the wave propagation speed and the source location. The arrival time is recorded at the receiver after an artificial source is excited at predefined event points. The TOAs are computed for each signal received from every projection angle. This data is input into the measurement algorithm to reconstruct a spatial map of locally varying wave speeds within the specimen [8].

The Algebraic Reconstruction Technique (ART) is the most widely used method for this purpose. Simultaneous Algebraic Reconstruction Technique (SART) and Simultaneous Iterative Reconstruction Technique (SIRT) are closely related iterative approaches [5]. The ART formulation, as shown in Eqs. (1), (2), and (3), iteratively updates the estimated slowness values, $S_{ij} = 1/C_{ij}$, for the discrete tomography cells (i, j), until the calculated arrival times t_p for ray p ($p = 1, 2, \ldots, N_p$) closely match the measured arrival times T_p.

In this process, the path lengths l_{ij}^p of each ray p through tomography cell (i, j) and the calculated arrival times from the k^{th} iteration are used to estimate updated slowness values for iteration $k + 1$.

$$t_p = \sum_{i,j} \left(S_{ij}^k \, l_{ij}^p \right) \tag{1}$$

$$\Delta S_{ij} = \frac{(T_p - t_p)\, l_{ij}^p}{\sum_{i,j} \left(l_{ij}^p \right)^2} \tag{2}$$

$$S_{ij}^{(k+1)} = S_{ij}^k + R \cdot \Delta S_{ij} \tag{3}$$

All tomography cells (i, j) that are crossed by ray p are subject to the combination of Eqs. (1), (2), and (3). The relaxation parameter R is used to boost the strength of the iteration. On a ray-by-ray basis, ART adjusts the slowness in each cell.

3. EXPERIMENTAL METHODOLOGY

3.1. Experimental Procedure

This analysis employed AET to visualize internal damage in a homogeneous aluminum structure. Initially, the AE transducer was placed on the specimen to capture the signals generated from controlled excitation points. The source transducer was positioned on the same surface of the specimen, producing AE events at sixteen different projection angles to ensure comprehensive coverage. The AE signals were recorded using the receiving transducer of the aluminum plate at corresponding receiver locations. Each excitation point was stimulated five times, and the averaged response was used to enhance measurement accuracy. A total of 16-ray coverage was implemented for slowness calculation, facilitating a moderate-resolution tomographic reconstruction of internal damage. The TOA of the waves was calculated using the Akaike Information Criterion (AIC) method for accurate localization of acoustic events. Wave slowness was calculated iteratively with TOA data as input to the AET algorithm for damage visualization reconstruction. Since the quality of the reconstructed damage image depends on the accurate estimation of the slowness, an iterative process was adopted to enhance the values. This experimental approach establishes a systematic approach for AE-based imaging in homogeneous structures and provides the necessary information for effective damage detection and visualization.

3.2. AE data acquisition system

Figure 1 presents the geometry and the projection of the AE signals on the experimental surface (16 cm × 16 cm), divided into a 4 by 4 array of unknown pixels with the 16 linear projections that were used in this experiment. The same experiment was also followed for the damaged surface. In Fig. 1, Event1-16 represents the artificial events that occurred within the aluminum block (45 cm × 45 cm × 1.5 cm), while T1-16 denotes the TOA for each event along its respective direction. This experimental configuration allowed for a comprehensive analysis of acoustic wave propagation within the homogeneous aluminum block, providing valuable data for the reconstruction of the material's internal structure and potential defects. AE tomography involves transmitting signals from several sources to receivers placed around the study area of the specimen. In traditional acoustic tomography, sound waves travel from multiple sources to receivers positioned at various locations around the specimen (Fig. 1). Fig. 1 illustrates a two-dimensional representation of the specimen under examination. The study area is divided into a grid of cells, where, initially, the propagation speed of AE signals is considered uniform across all cells. Additionally, a straight-ray model is assumed for the travel paths between sources and sensors before the iterative process begins. Table 1 and 2 represents the material properties and AE signals acquisition parameters.

Table 1: Material Properties

Material Parameter	Value
Poisson ratio	0.33
Density (ρ), kgm^{-3}	2680
Shear modulus (Pa)	6.93×10^9

Table 2: AE Signal Acquisition Parameters in the Test

Sensor	R15-alpha
Threshold level (dB)	50
Preamplifier (dB)	40
Filter (kHz)	100–400
Sample rate	10 MSPS
Pre-trigger	256000

3.3. Experimental Setup

An aluminum block was utilized to reconstruct the slowness mapping within a homogeneous material. The experimental setup employed one sensor as a transmitter and another as a receiver. A single sensor was used to collect a signal for each event, and time, from a definite direction. Each time, the source and receiver sensors were moved in a straight ray path in a different projection angle to collect the signals from all possible projections. Based on the projection, a total of 16 linear equations were used to reconstruct the 16 unknowns. The block diagram of the experimental setup is shown in Fig. 2. The function generator was used as the input stimulator using the

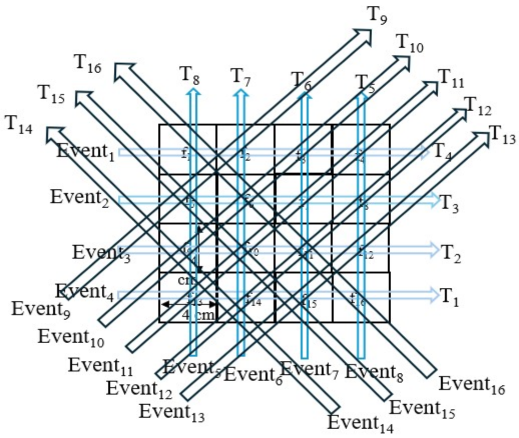

Figure 1: Layout of the experimental specimen.

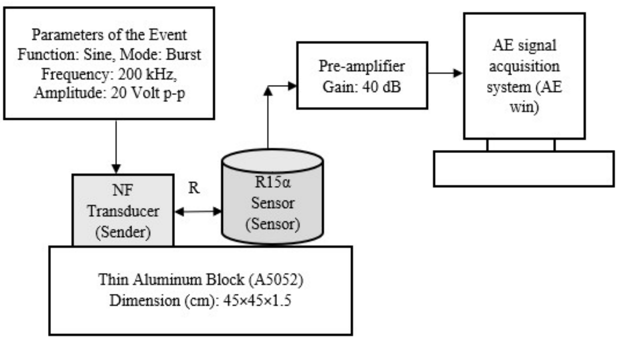

Figure 2: Block diagram of the experimental setup.

AE sensor (Model: AE-900S-WB, NF Corporation, Japan) and the R15 alpha sensor was used as a receiver and then connected to the AE data acquisition system with a pre-amplifier. This experimental configuration allowed for a comprehensive analysis of AE wave propagation within the homogeneous aluminum block, providing valuable data for the reconstruction of the material's internal distribution of the slowness. Figs. 3, and 4 represent the experimental specimen both for non damaged and damaged surfaces.

4. TIME OF ARRIVAL CALCULATION

Time of Arrival (TOA), which refers to the travel time of an AE signal from its source to a sensor, is a widely used method for identifying the location of a damaged region. However, analyzing wave propagation paths becomes increasingly complex in geometrically intricate structures. Accurate arrival time estimation is essential to minimize visualization errors. Common methods for TOA determination include First Threshold Crossing (FTC) and Maximum Amplitude.

Since AE signals consist of multiple wave modes, such as P-waves and S-waves, the utilization of maximum amplitude for localizing the source in complex surfaces may introduce errors because of differences in the wave velocity modes. Conversely, the FTC approach is capable of picking up precisely the arrival time of the faster P-wave and thereby reducing ambiguity in source localization. However, FTC is similarly susceptible to error in picking up onset time depending on the selected threshold value. To ensure precision, in this research work the AIC approach is used for TOA estimation. Autoregressive AIC (AR-AIC) algorithm, being used for the detection of the onset, is efficient in computations, stable, and can be automatically implemented and is a consistent choice for refining AE signal analysis [9, 10, 11]. AR-AIC methodology details are provided in the following section.

4.1. Autoregressive Akaike Information Criterion (AR–AIC) Method

The accuracy of the Time of Arrival (ToA) estimation is of great significance in Acoustic Emission Tomography (AET). In this article, the onset of AE signals was determined using a model in which the signal is treated as an autoregressive (AR) process. This approach is based on the assumption that the AE time series comprises two locally stationary processes: an initial segment of low-amplitude random noise, followed by a high-amplitude impulse corresponding to the first arrival of the AE event.

This method, known as the Autoregressive Akaike Information Criterion (AR-AIC), has been extensively applied in seismology for P-wave phase detection. Originally introduced by Akaike in 1973 and further refined by Maeda, it has recently been adopted in AE research to improve the accuracy of onset time estimation [12].

In Fig. 5, a time series of length *nsamp* is assumed to consist of two pseudo-stationary segments: the first from 1 to k, and the second from $k+1$ to *nsamp*. A pseudo-stationary process maintains a constant mean and variance within the observation window. The initial segment represents background noise, while the latter segment reflects the propagating energy following the AE event. The first

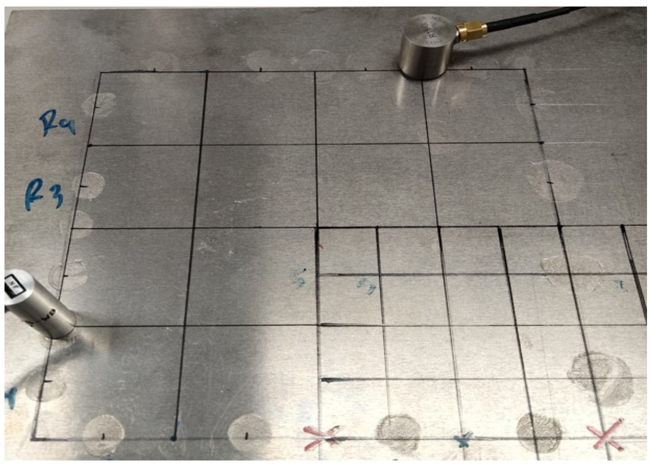

Figure 3: Experimental specimen (AL) without damage.

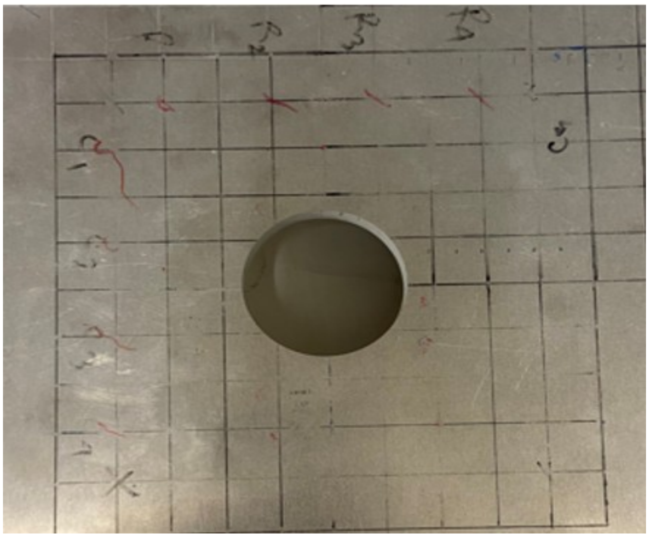

Figure 4: Experimental specimen (AL) with damage.

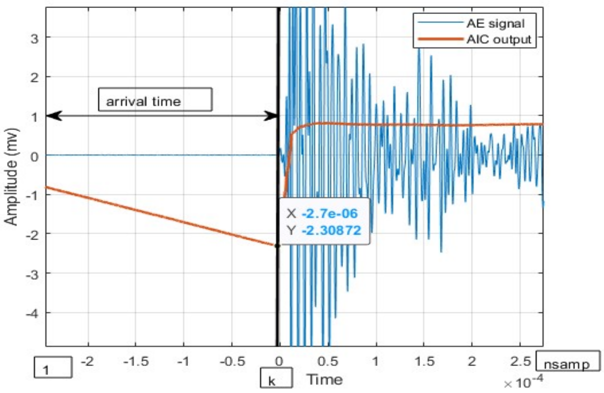

Figure 5: Detection of TOA of the collected signal.

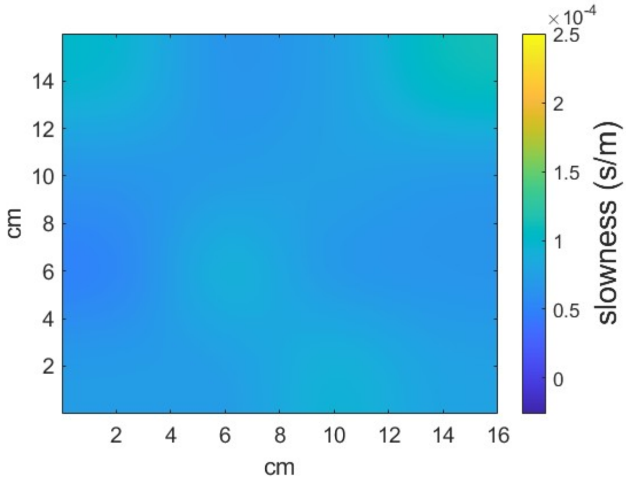

Figure 6: No visible damage presence in the tomographic image.

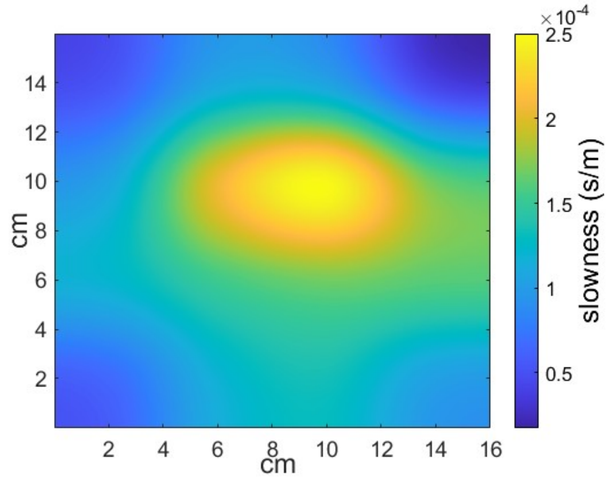

Figure 7: Presence of damage (black dotted circle) in tomographic image.

arrival time of the AE signal is estimated by identifying the global minimum of the AIC function. AIC is computed at each sample point and provides a robust method for automatic arrival detection, even under varying signal-to-noise ratios [13].

For a sequence y of length N, the AIC is calculated as:

$$\begin{aligned} AIC(k) &= k \times \log\left(\mathrm{var}(y(1{:}k))\right) \\ &+ (nsamp - k) \times \log\left(\mathrm{var}(y(k{+}1{:}nsamp))\right) \end{aligned} \tag{4}$$

5. RESULTS

The AET method suggested and coupled with an IRA was employed to reconstruct the internal slowness distribution of an aluminum sample in damaged and undamaged conditions. AE signals were recorded by a single sensor with 16 linear projections at different angles, where TOA measurements were utilized as fundamental input to the tomographic reconstruction algorithm. After processing the AE data, slowness distribution maps were created, which allowed for comparative analysis of acoustic wave propagation characteristics in intact and damaged states. The reconstructed tomographic images exhibited distinct differences, which attested to the presence of internal defects as revealed by the analysis of wave propagation behavior. For the undamaged aluminum sample, the reconstruction from tomography revealed a near-uniform slowness distribution in Fig. 6, which represents homogeneous wave propagation without visible structural damage. This homogeneity validates the reliability of the AE data acquisition system and reconstruction method. The reconstructed images for the damaged aluminum sample revealed localized increases in values of slowness in Fig. 7, which reflects the presence of damage. The appearance of the circular defect altered the wave propagation path, forcing AE waves to circumvent the defective area, leading to longer travel times and higher slowness values. These slowness distribution changes confirmed the ability of AET to visually inspect and detect internal defects through the analysis of wave travel-time anomalies. The obvious contrast between the slow fields in defective and undamaged regions underscores the technique's sensitivity to identify and describe defects with high accuracy. The findings confirm the effectiveness of IRA-based AET for non-destructive material testing, particularly in homogeneous metal structures. The findings altogether support the validity of the presented ART-based AE tomography paradigm in non-destructive testing applications, with significant implications for industries requiring real-time structural health monitoring, including aerospace, automobile, and civil engineering. Stability of the suggested approach also certifies AET as a reliable imaging method for application in damage assessment, leading into future advanced NDE techniques for use in engineering.

6. CONCLUSIONS

AET has been shown to be a valid NDE tool by enabling the visualization of wave slowness distribution within a material. In this paper, AET was successfully applied on an aluminum block, demonstrating its efficacy in detecting and visualizing internal damage. With the ART, the study was able to successfully image the internal structure, highlighting regions of greater slowness that indicate damage. The results confirm the potential of AET SHM, particularly in homogeneous metallic structures. The findings provide valuable information on wave propagation behavior, reinforcing the usefulness of the technique in assessing material integrity. Additionally, the ability to accurately reconstruct damage zones places AET as a viable technique for visualization and detection of defects in industrial applications.

This work forms a foundation for the application of AET to more heterogeneous and complex material systems, like composites and multilayered media. The theme of future research will be advancing the reconstruction algorithms to gain even higher spatial resolution and numerical efficiency. The inclusion of machine learning-based methods can further enhance defect visualization accuracy and widen the field of application of AET in engineering disciplines.

In summary, AET, when combined with iterative reconstruction algorithms like ART, is a promising method for improving NDE techniques, with important contributions to material and biological science, and structural engineering applications.

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