

Accelerated noncontact guided wave array imaging via sparse array data reconstruction

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Abstract

Noncontact guided wave array imaging with a scanning laser Doppler vibrometer (SLDV) is an effective tool to detect and locate defects within a plate-like structure, as it obviates the need for installing, calibrating, and maintaining a transducer array. However, it requires collecting guided wave signals through scanning across dense spatial grid points to avoid non-defect artifacts in the array image, which is time-consuming. In this paper, we present an accelerated noncontact guided wave array imaging method that does not require dense scanning array while providing defect imaging performance comparable to the dense scanning case. In our approach, sparse scanning measurements at only a small number of points are carried out first for fast guide wave data acquisition. Then, dense guided wave array data is reconstructed from these sparse array measurements using a sparsity-promoting optimization technique, followed by delay-and-sum (DAS) beamforming to image defects within a test structure. We validate this method with laboratory experiments on composite plate specimens with multiple defects. The results demonstrate that defects within a composite plate can be successfully detected and located using sparsely sampled guided wave array measurement data. Such a significant reduction in the number of required measurement points enables accelerated noncontact guided wave array imaging.

1. Introduction

Guided waves are widely employed to inspect confined structures like plates, as they propagate a long distance with low energy loss [1,2]. Among various guided wave-based nondestructive evaluation (NDE) and structural health monitoring (SHM) techniques, guided wave array imaging has shown its effectiveness in defect imaging (*i.e.* detection and localization) from a large inspection area with limited access [3–7]. Using a guided wave array, defect imaging is typically carried out by delay-and-sum (DAS)-based beamforming, where a predefined time delays are applied to array elements for excitation and sensing of guided waves; the measured signals are then summed to create an image in which defects within an inspection region of the test structure are visualized as high pixel intensities. Post-processing-type DAS beamforming can also be performed by applying the DAS principle to process a full matrix of guided wave excitation-sensing array data. In spite of the effectiveness of the guided wave array imaging technique, technical limitations remain to implement the technique. First, an array of multiple contact-type piezoelectric transducers such as lead zirconate titanate (PZT) patches are employed, which is time and labor-consuming to install, calibrate, and maintain. Furthermore, modifying the array configuration is difficult, once the guided wave array that is adhesively installed on a test structure.

To address these challenges, noncontact guided wave array imaging with a scanning laser Doppler vibrometer (SLDV) has been proposed in recent studies [8–10]. Taking advantages of the SLDV, noncontact guided wave array imaging provides significant advantages over the contact-type array imaging technique. First, array installation is not needed as the guided wave responses are obtained by scanning measurements with the SLDV, which reduces costs in installation, calibration, and maintenance of ultrasonic transducers. In addition, high spatial sensing resolution can be achieved as well as flexibility in array configurations. SLDV-based noncontact guided wave array imaging has been demonstrated successfully across various engineering materials including metals and carbon fiber-based composites [8,9]. However, there is still a limitation of the noncontact guided wave array imaging technique that hinders its wide acceptance in real-world structural inspection. That is, guided wave responses need to be collected

across a dense scanning grid points to avoid non-defect artifacts that can lead to false defect indications in the obtained in the DAS beamforming image. Performing dense scanning measurements is time-consuming, making it difficult to practically inspect real-world large structures.

Research efforts have been made to accelerate guided wave scanning measurements using compressed sensing (CS) techniques [14–18]. In these studies, guided wave responses sparsely collected across a few pre-defined spatial sensing points are used to reconstruct dense guided wavefield data as if they were collected from a much denser sensing grid. Assuming that a guided wavefield data can be represented sparsely with a certain basis, this can be achieved by solving a system of underdetermined linear equations with a sparsity-promoting optimization technique [19,20]. Considering that the total number of guided wave signals collected by scanning measurements is linearly proportional to the time duration for data acquisition, compressed sensing can accelerate scanning measurements of guided waves significantly. Studies have shown its effectiveness in rapid guided wavefield data acquisition, and near-field defect visualization within a reconstruction grid has been demonstrated [15–17]. However, these methods aim to visualize defects only within the scanned area (or the reconstruction grid), making it challenging to inspect a larger area outside the scanned area.

In separate efforts, defect imaging has been carried out using a sparse guided wave array where a few transducers are loosely distributed over the inspected structure [11–13]. Once guided wave signals are obtained from all transmit-receive pairs (i.e. sparse array data), defect imaging can be carried out with various algorithms including DAS imaging [12], multiple signal classification (MUSIC) [13], and sparsity-promoting optimization [11]. Due to the small number of array elements for these techniques, array data acquisition time can be short while providing a reasonable defect imaging performance. However, the sparse guided wave array approaches typically require baseline data to extract scattering wave components, which is not always available in practice.

In this study, we propose an accelerated noncontact guided wave array imaging approach via CS-based guided wave array data reconstruction. Unlike previous CS studies for guided wavefield imaging that

are applied to visualize defects within a scanned area only, this study makes use of a CS technique for far-field defect imaging that enables imaging a much larger area than the existing methods. The proposed approach combines an SLDV-based noncontact sensing, a CS-based data reconstruction, and far-field defect imaging techniques to accelerate guided wave array data collection while imaging a large inspection area with limited sensor access at the same time. First, dense noncontact guided wave array data is reconstructed from a sparsely collected guided wave signal set by solving a CS problem with a sparsity-promoting optimization technique. Then, post-processing-type DAS beamforming is carried out using the reconstructed array data to image defects within a large inspection area. The proposed approach provides the following advantages to guided wave array imaging: (1) accelerated noncontact guided wave array imaging can be achieved while the performance of defect imaging is not meaningfully compromised; (2) the proposed guided wave array imaging technique does not require baseline data in the defect imaging process; and (3) the defect imaging performance is robust against the reconstruction error of guided wave array data.

2. Accelerated noncontact guided wave array imaging

In this section, the proposed accelerated noncontact guided wave array imaging method is described. We introduce an overview of the proposed approach, followed by the details of each step of the method.

2.1. Overarch of the proposed accelerated noncontact guided wave array imaging method

The overview of the proposed accelerated noncontact guided wave array imaging method is illustrated in **Figure 1**. In Step 1, a sparse guided wave array data is collected using an SLDV. From a predefined 2-D spatial sensing grid, guided wave responses are acquired across randomly under-sampled sensing points. In **Figure 1**, light green dots represent sparse measurement points and gray dots not measured points. In Step 2, dense guided wave array data is reconstructed from the sparse array data acquired in Step 1 with the mixed l_{12} minimization technique that is a sparsity-promoting optimization

technique. In Step 3, DAS beamforming is carried out to create a defect image using the reconstructed guided wave array data computed in Step 2.

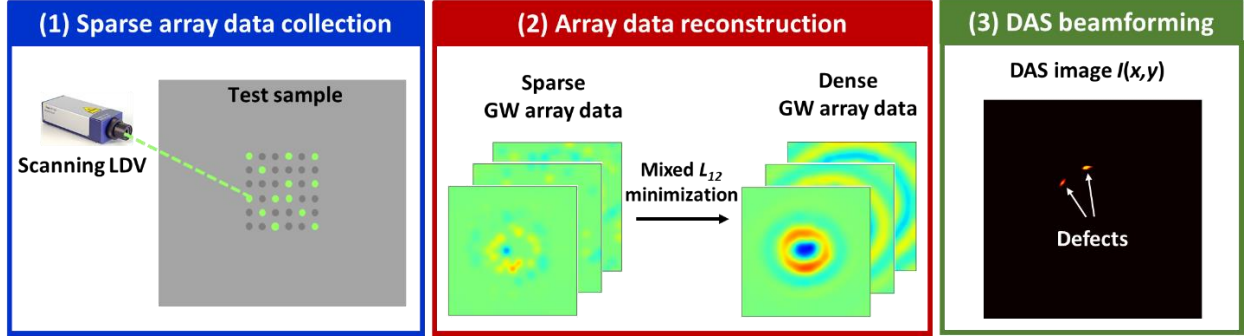


Figure 1. Overview of the proposed accelerated noncontact guided wave array imaging method. Sparse guided wave array data is collected using an SLDV. Then, dense guided wave array data is reconstructed using the collected sparse array data via a sparsity-promoting optimization technique. Finally, a defect image is computed through DAS beamforming using the reconstructed array data.

2.2. Reconstruction of guided wave array data via sparsity-promoting optimization

In the theory of compressed sensing, a signal that is sparse in a certain basis can be accurately reconstructed from a few linear measurements [19,20]. This is applicable to guided wave array data reconstruction, as a set of guided wave signals can be sparsely represented in various bases such as the Fourier basis [14] and modal solution-based basis [15]. Here, we propose a guided wave array data reconstruction technique taking advantages of the sparsity of guided wave array data.

The proposed reconstruction approach is carried out by solving multiple measurement vectors (MMV) CS problem with a sparsity-promoting optimization technique, as schematically illustrated in

Figure 2. The sparse measurement matrix where $\mathbf{Y} \in \mathbb{R}^{N \times R}$ can be expressed as

$$\mathbf{Y} = \Phi \mathbf{X}, \quad (1)$$

where $\Phi \in \mathbb{R}^{N \times M}$ is the down-sampling matrix that linearly maps $\mathbf{Y}$ and the unknown dense measurement matrix $\mathbf{X} \in \mathbb{R}^{M \times R}$. Here, each row vector $y_k^T \in \mathbb{R}^{1 \times R}$, $k = 1, \dots, N$ of $\mathbf{Y}$ represents a guided wave signal collected from a sparse sensing and $x_k^T \in \mathbb{R}^{1 \times R}$, $k = 1, \dots, M$ of $\mathbf{X}$ represents a guided wave signal from a dense sensing point. Assuming that x_k^T can be sparsely represented with a basis $\mathbf{B} \in \mathbb{R}^{M \times P}$, the MMV-CS problem is formulated as

$$\mathbf{Y} = \Phi \mathbf{B} \mathbf{A} = \Psi \mathbf{A}, \quad (2)$$

where $\mathbf{A} \in \mathbb{R}^{P \times R}$ is the basis coefficient matrix that is the sparse representation of the dense measurement matrix $\mathbf{X}$. The multiplication of Φ and $\mathbf{B}$ gives the sensing matrix $\Psi \in \mathbb{R}^{N \times P}$. Note that $\mathbf{A}$ is row-sparse, meaning that only a few rows of $\mathbf{A}$ have non-zero values. In this study, a two-dimensional (2-D) discrete cosine basis is used as $\mathbf{B}$ considering it is a simple and universal basis that can be applied to various CS problems [17]. Also, theoretical guided wave response solutions have sinusoidal terms that are similar in shape to discrete cosines.

Once the MMV-CS problem is formulated, the solution $\mathbf{A}$ is obtained using a sparsity-promoting optimization technique basis pursuit (BP) that minimizes the mixed $l_{1,2}$ norm of $\mathbf{A}$, expressed by

$$\min_{\mathbf{A}} \|\mathbf{A}\|_{1,2} \quad \text{subject to } \Psi \mathbf{A} = \mathbf{Y}, \quad (3)$$

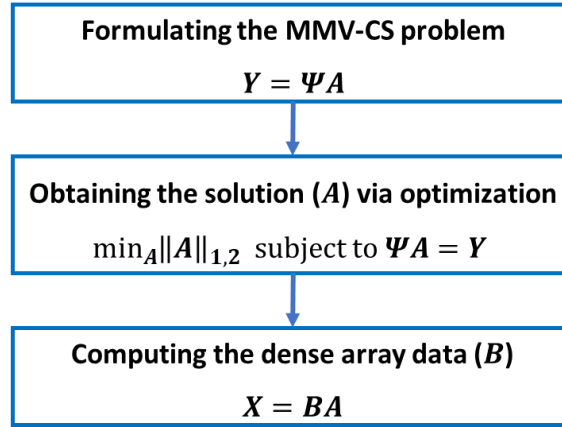
where $\|\mathbf{A}\|_{1,2}$ is given by

$$\|\mathbf{A}\|_{1,2} = \sum_{j=1}^P \|A^{j \rightarrow}\|_2, \quad (4)$$

where $A^{j \rightarrow}$ is the j^{th} row vector of $\mathbf{A}$. To obtain a BP solution $\mathbf{A}$ for the MMV-CS problem, a well-known solver SPGL1 [21] is used in this study. Finally, the reconstructed dense guided wave array data $\mathbf{X}$ is obtained by matrix multiplication between the basis and BP solution matrices, given by

$$\mathbf{X} = \mathbf{B} \mathbf{A}. \quad (5)$$

To obtain a satisfying BP solution, the sensing matrix Ψ is required to satisfy the restricted isometry property (RIP) with the RIP constant smaller than unity [22,23]. This is typically satisfied in practice when Ψ is orthonormal. In this study, the orthonormality of Ψ is satisfied by performing random sparse sampling across a dense 2-D scanning grid and using the 2-D discrete cosine basis.



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133 **Figure 2.** Schematic illustration of the guided wave array data reconstruction method.

2.3. Delay-and-sum beamforming using the reconstructed guided wave array data

Once dense guided wave array data is reconstructed in Step 2, a defect image $I(x, y)$ is computed using a DAS-based beamforming algorithm. Here, the reconstructed dense guided wave array data represents receiver phased array data obtained across all the measurement points over the full dense 2-D scanning grid. A synthetical beam focusing is then carried out to compute $I(x, y)$ given by

$$I(x, y) = \left| \sum_{rx=1}^K h_{rx}(\tau_{rx}(x, y)) \right|, \quad (6)$$

where h_{rx} is the reconstructed guided wave signal for a receiver point (rx) , $\tau_{rx}(x, y)$ the time delay applied to the signal h_{rx} for synthetical beam focusing on an image pixel at (x, y) , and K the total number of receivers. $\tau_{rx}(x, y)$ is computed as

$$\tau_{rx}(x, y) = \frac{\left| \sqrt{x^2 + y^2} + \sqrt{(x_{rx} - x)^2 + (y_{rx} - y)^2} \right|}{c_g}, \quad (7)$$

where (x_{rx}, y_{rx}) is the position of a receiver when the excitation for guided wave generation is applied at $(0,0)$, and c_g is the group velocity of the incident guided wave mode. In the DAS image $I(x, y)$, pixels with a high intensity indicate regions including possible defects.

In this study, the fundamental anti-symmetric (A0) Lamb wave mode is used considering that it is the dominant guided wave mode at the center frequency of excitation (120 kHz) for the tested composite laminate sample as well as it is less dispersive across the excitation frequency band.

3. Experimental validation

3.1. Experimental setup

The proposed accelerated guided wave array imaging method is validated using the guided wave array data obtained by laboratory experiments on an 8-ply CFRP composite laminate plate ([0, 45, 90, 135]_s). **Figure 3a** shows the backside of the tested CFRP composite plate. At the center of the plate, a PZT

patch (Piezo.com 5H) with a dimension of $9\text{ mm} \times 9\text{ mm} \times 0.267\text{ mm}$ is installed to generate guided waves. An artificial defect was introduced by attaching a steel bolt with adhesive as seen in **Figure 3a**. Two defect scenarios are considered: (1) a plate with one defect located at Position D1 (0, 100) mm and (2) a plate with two defects located at Positions D1 and D2 (-70.7, 70.7) mm.

Figure 3b shows the experimental setup to collect the guided wave array data from the tested composite plate. An arbitrary waveform generator (BK Precision, 4047B) generates a 3-cycle tone burst excitation signal at the center frequency of 120 kHz. The generated excitation signal is then amplified to 35.5 V by a power amplifier (Krohn-Hite, 7602M) to be applied to the installed PZT for guided wave generation. An LDV (Polytec, MLV-I-120 (sensor head) and OFV-5000 Xtra (controller)) is used to measure the corresponding guided wave responses from the tested composite plate. Scanning measurements were implemented with dual-axis galvanometer (Thorlabs, GVS002) across 21×21 sensing points with 2.3 mm spacing in both the x and y directions. The sensing points act as a 2-D receiver phased array.

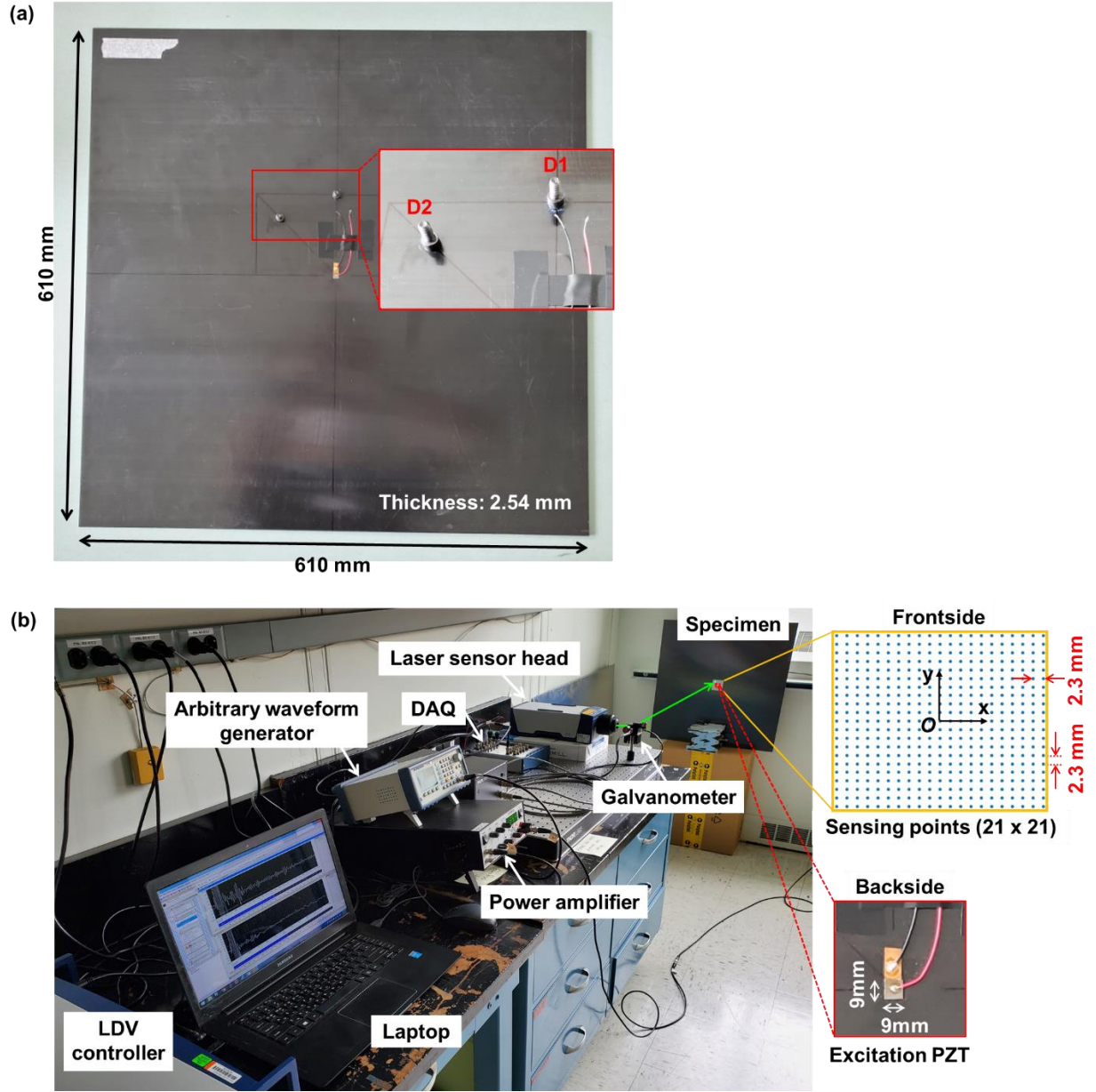


Figure 3. Experimental setup to collect guided wave array data from a CFRP composite laminate: (a) the back side of the tested CFRP plate and (b) a noncontact guided wave array data acquisition setup.

3.2. Results and discussion

The proposed accelerated noncontact guided wave array imaging method was validated using the array data collected from the CFRP composite laminate sample shown in **Figure 3a**. As reference full dense array data, guided wave responses were measured across the 21 x 21 sensing points for the two defect cases. Then, sparse array data were obtained by applying a sparse sampling mask to the reference full dense array

data. An example sparse sampling mask with a sparse sampling ratio (R_{sparse}) of 30 % is shown in **Figure 4a**. R_{sparse} is defined as

$$R_{sparse} [\%] = \frac{N}{M} \times 100, \quad (8)$$

where N is the number of sensing points for a sparse array and M that for a full dense array. In **Figure 4a**, white pixels represent sampled spatial points and black pixels unsampled spatial points from the 21 x 21 sensing grid points shown in **Figure 3b**. Using the sparse array data, dense guided wave array data was reconstructed with the procedure described in Section 2.2. An example time-domain guided wave signal selected from the reconstructed array data (indicated as ‘Reconstructed’) is compared with the reference signal from the reference full dense array data (‘Dense’) in **Figure 4b**. Note that the selected sensing point for the reconstructed array data is originally unsampled point (i.e., one of the black pixels in **Figure 4a**). In **Figure 4b**, the reconstructed guided wave signal shows good agreement with its corresponding reference signal from the original dense array data.

To visualize the overall reconstruction quality, the reconstructed guided wave array data at a certain time instance ($t = 145 \mu s$) is shown in **Figure 4c**, and its corresponding reference dense array data at $t = 145 \mu s$ is shown in **Figure 4d**. The presented array data can be interpreted as guided wavefield snapshots at the time instance. In the figures, the reconstructed array data (**Figures 4c**) shows good agreement with the reference dense array data (**Figures 4d**), showing the spatial wavefield pattern of the reconstructed data is similar to that of the reference data.

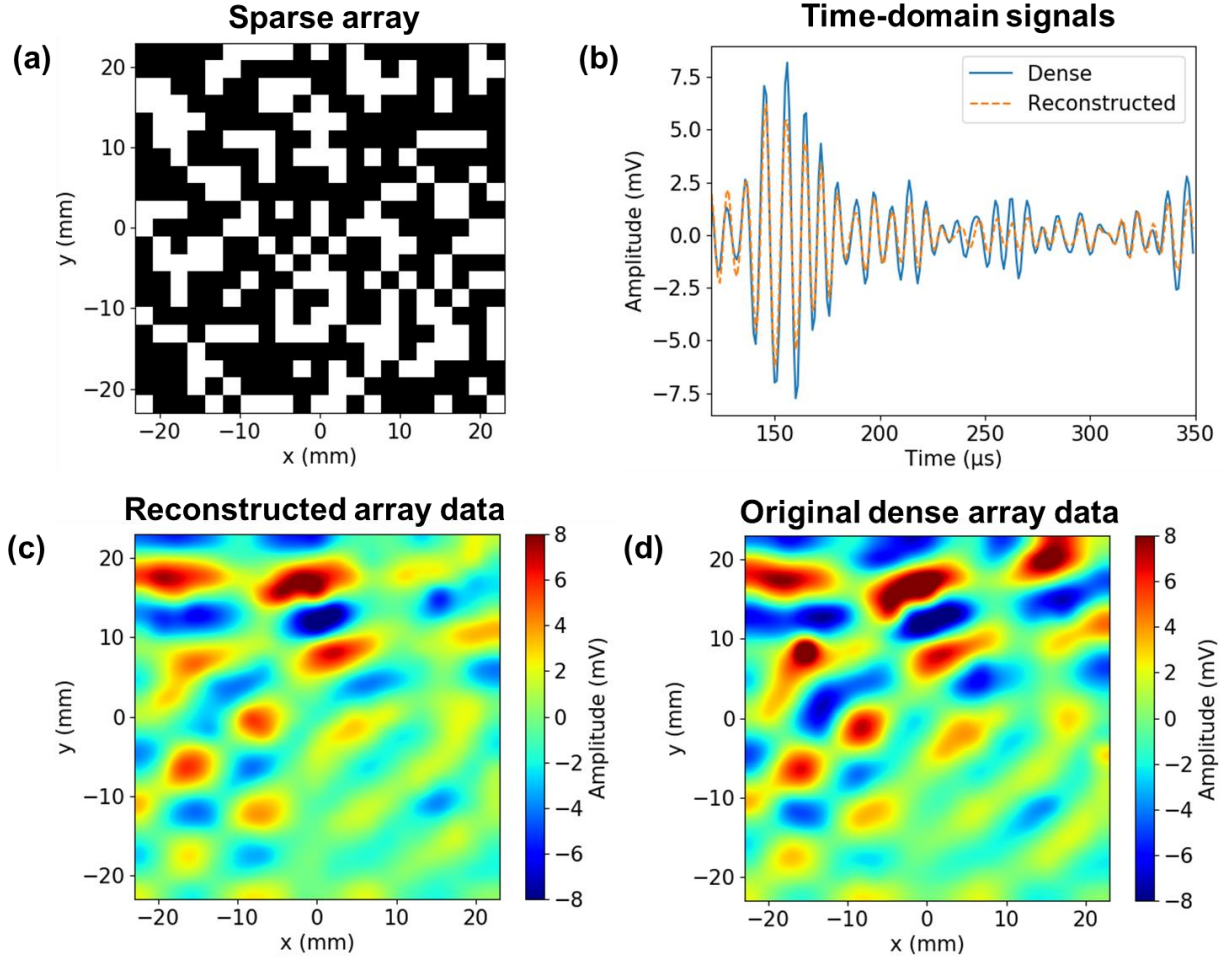


Figure 4. Guided wave array data reconstruction results: (a) the sparse sampling mask to obtain a sparse guided wave array data, (b) an example of reconstructed time-domain signal, (c) the reconstructed array data at $t = 145 \mu\text{s}$, and (d) the original dense guided wave array data at $t = 145 \mu\text{s}$. In (a), white pixels represent sampled sensing points and black unsampled sensing points from the 21×21 array sensing grid points.

Defect imaging results obtained by the proposed approach are shown in **Figure 5**. DAS beamforming images computed using the reconstructed dense guided wave array data for the two defect cases (D1 only and D1 & D2) are shown in **Figures 5a** and **b**, respectively. For the reconstructed array data for both defect cases, R_{sparse} was 40%. Each DAS beamforming image was normalized by its maximum pixel intensity. In **Figures 5a** and **b**, the defects shown in **Figure 3a** are clearly observed from the computed DAS beamforming images. The high intensity objects shown in the DAS images match well with the expected defect positions. The DAS beamforming images obtained with the reference dense array data are shown in **Figures 5c** and **d**. It is seen that the DAS images computed with the reconstructed array data

(Figures 5a and b) exhibit good agreement with those computed with the reference dense array data (Figures 5c and d) in the clarity of defect indications. These results demonstrate that the proposed approach enables defect imaging with sparsely sampled guided wave array data, making it possible to accelerate guided wave array imaging processes. To further investigate the utility of the dense array data reconstruction step (Step 2 in Figure 1) in the proposed approach, DAS images for the two defect cases computed using the sparse array data omitting the reconstruction step are shown in Figures 5e and f, respectively. In both defect cases, false defect indications (high-intensity artifacts) are observed, which compromises the credibility of defect detection. These results demonstrate that the data reconstruction step in the proposed approach significantly improves defect imaging performance by reducing the possibility of false defect indications.

The defect localization accuracy of the proposed approach is summarized in Table 1. Localized defect positions for the two defects (D1 and D2) using the proposed approach are compared with actual defect positions. The defect positions were obtained by picking local maxima from the defective regions shown in Figure 5b. To quantify the localization error, the relative distance error between localized and actual defect positions are computed by

$$Error [\%] = \sqrt{\frac{(x_l - x_{true})^2 + (y_l - y_{true})^2}{x_{true}^2 + y_{true}^2}} \times 100, \quad (9)$$

where (x_l, y_l) and (x_{true}, y_{true}) are localized and actual defect positions, respectively. Although not significantly high, some degree of localization error was observed. In this study, a uniform group velocity (1500 m/s) of the A0 mode neglecting its angular dependency is assumed for simplicity. The defect localization error may be reduced if the angular dependency of the A0 mode group velocity is considered.

Table 1. A summary of defect localization accuracy for the two defects (D1 and D2).

	Localized position		Actual position		Error (%)
	x (mm)	y (mm)	x (mm)	y (mm)	
D1	-9.3	112.1	0	100	15.3
D2	-77.6	75.7	-70.7	70.7	8.5

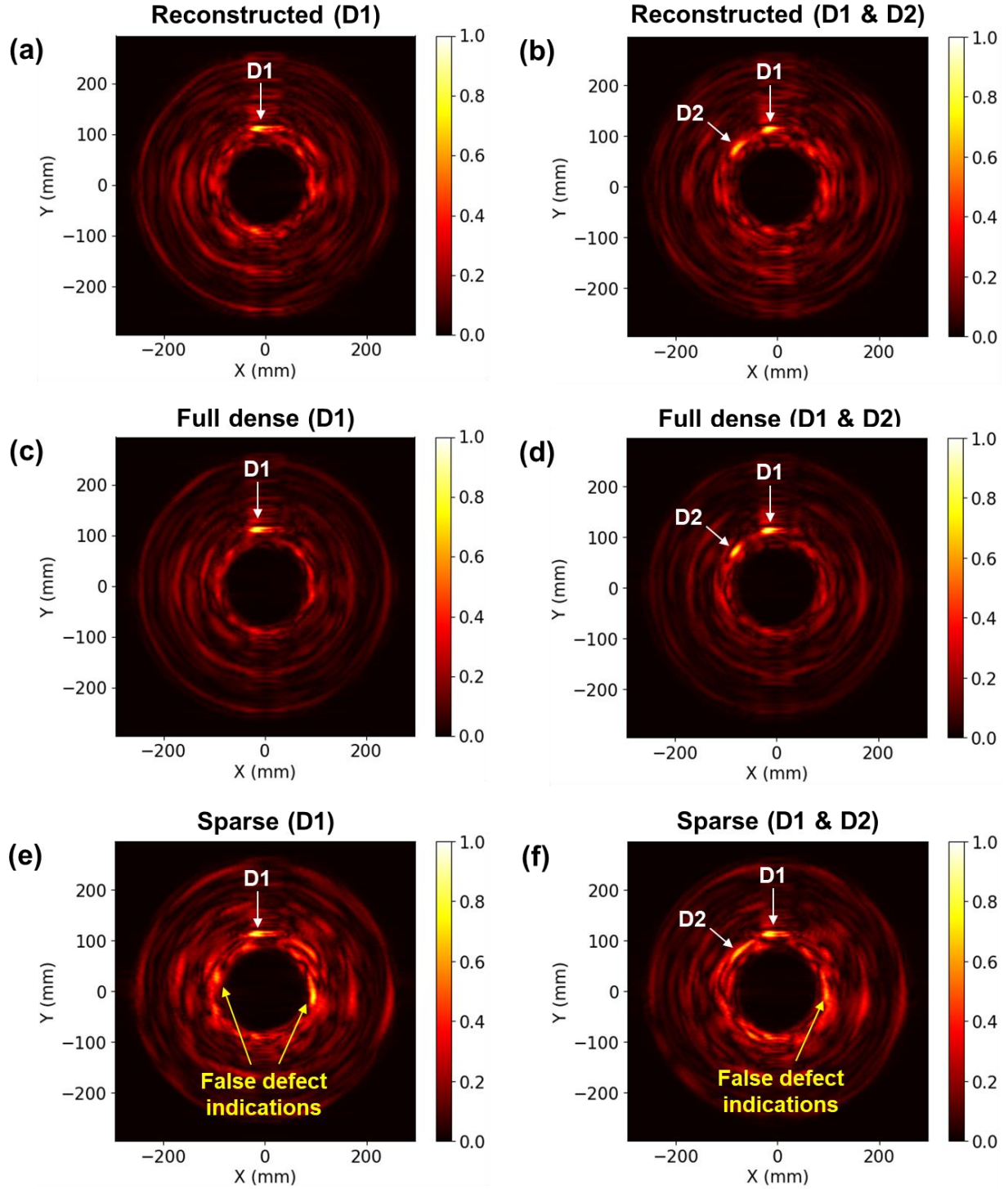


Figure 5. Defect imaging results via delay-and-sum (DAS) beamforming: DAS images computed using reconstructed dense array data for (a) the one-defect case (D1) and (b) two-defect case (D1 and D2); DAS images computed using full dense array data for (c) D1 and (d) D1 and D2; DAS images computed using sparse array data for (e) D1 and (f) D1 and D2. For sparse array data sampling, 40% of the full dense array data were randomly sampled.

Effects of the reconstruction accuracy for guided wave array data on the DAS imaging performance are discussed. **Figure 6a** shows the relationship between the sparse under-sampling ratio R_{sparse} and the pick signal-to-noise ratio (PSNR) that measures the reconstruction accuracy for guided wave array data. PSNR is computed as

$$PSNR \text{ [dB]} = 20 \log_{10} \left(\frac{\max(|X|)}{\sqrt{\frac{1}{M} \|X_{ref} - X\|_2^2}} \right), \quad (10)$$

where X is the guided wave array data reconstructed from the sparse array data and X_{ref} the reference full dense array data. **Figure 6a** shows that PSNR gradually increases as R_{sparse} increases, indicating that a high reconstruction accuracy can be obtained at a cost of more sensing points for sparse array data acquisition.

Next, effects of the array data reconstruction accuracy on the beamforming imaging performance are discussed. **Figure 6b** shows the relationship between the reconstruction accuracy evaluated by PSNR and beamforming imaging performance evaluated by the intersection of union (IoU). IoU also known as the Jaccard similarity coefficient is computed by

$$IoU = \frac{|P \cap P_{ref}|}{|P \cup P_{ref}|}, \quad (11)$$

where P and P_{ref} represent a set of pixels with their pixel intensities equal or greater than 0.5 in a normalized DAS image computed from the reconstructed array data and reference dense array data, respectively. Note that IoU measures how well the defective regions indicated in a DAS image for reconstructed array data overlap those indicated in a DAS image for its corresponding reference dense array data. An IoU value closer to one indicates a higher DAS imaging performance. Based on our empirical observations, we assert that IoU equal or higher than 0.3 indicates the number of defects and their locations are successfully identified in the DAS image for the reconstruction array data. **Figure 6b** shows that IoU increases as PSNR increases. In addition, this figure reveals that PSNR above 25 dB (30% of R_{sparse})

provides successful defect imaging performance (*i.e.* $\text{IoU} \geq 0.3$). Note that the sparse under-sampling ratio is proportional to the the total time duration to collect guided wave array data. For example, 30% of under-sampling takes 30% of the total time to acquire a full dense array data, considering that 30% of a guided wave signal set is needed to reconstruct a full dense array data. The results shown in **Figure 6** demonstrate that the proposed approach provides accelerated guided wave array imaging of defects by reducing the number of array elements significantly while maintaining a high defect imaging performance.

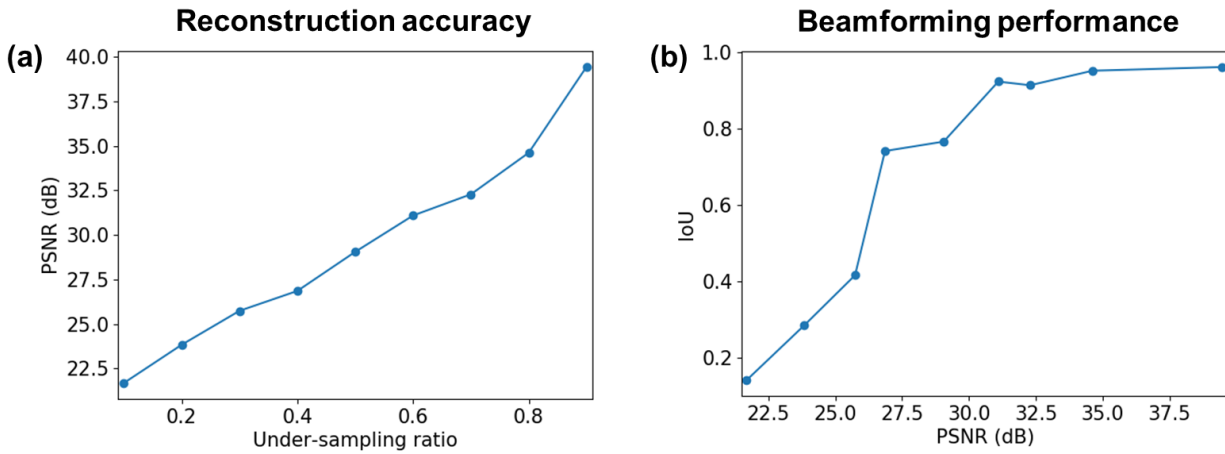


Figure 6. Effects of reconstruction accuracy on delay-and-sum beamforming performance: (a) peak signal-to-noise ratio (PSNR) as a function of sparse under-sampling ratio and (b) intersection over union (IoU) as a function of PSNR.

We discuss the difference between our accelerated guided wave array imaging approach with distributed sparse array-based defect imaging approaches. In distributed sparse array approaches [11,12], a few piezoelectric transducers are distributed loosely over a test plate structure. Due to the nature of the array configuration (pitch-catch type), guided wave signals collected by the distributed sparse array include forward- and back-scattering components that are mixed with direct arrivals and boundary reflections. As all these guided wave components are overlapped in a time-domain signal and not easily separable, scattering components needed for the defect imaging process are typically obtained by baseline subtraction. However, baseline data collected from the test structure when it is intact is not always available in practice. Our sparse guided wave array is a denser array where sensor elements are distributed near the excitation transducer element. Due to its pulse-echo type configuration, scattering components (most likely back-

scattering) are well separated from other wave components in a time-domain signal, and hence baseline subtraction is not needed. The absence of baseline requirements is the main advantage of the proposed sparse guided wave array imaging approach over existing sparse distributed array approaches. Once sparse guided wave array data is collected, dense array data is computationally reconstructed for improved defect imaging performance.

4. Conclusions and future work

In this study, we proposed an accelerated noncontact guided wave array imaging technique, where dense guided wave array data is reconstructed from sparse array data first, and then a DAS beamforming is carried out to image defects from plate-like structures. Based on the results presented in the paper, the following conclusions are drawn:

- (1) The proposed array data reconstruction method enables accurate reconstruction of dense guided wave array data from sparsely measured array data, providing PSNR above 25 dB;
- (2) The proposed guided wave array imaging method that combines array data reconstruction and DAS beamforming tasks can image defects from plate-like structures successfully with a reduced number of array sensing points; and
- (3) The reduced number of array sensing points achieved by the proposed method can accelerate guided wave array imaging work by reducing the time duration to acquire array data.

The proposed method enables successful defect imaging with fewer number of guided wave signals. However, the number of sparse sensing points is fixed at the measurement phase, and the fixed sensing points may not be the optimal for defect imaging. In future work, we will incorporate a deep reinforcement learning (DRL) technology for autonomous guided wave array imaging where the number of sparse sensing points are determined by a trained DRL agent.

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