Model-Based Iterative Reconstruction for One-Sided Ultrasonic Nondestructive Evaluation

Hani Almansouri, Singanallur Venkatakrishnan, Charles Bouman, and Hector Santos-Villalobos

Abstract—**One-sided ultrasonic nondestructive evaluation (UNDE) is extensively used to characterize structures that need to be inspected and maintained from defects and flaws that could affect the performance of power plants, such as nuclear power plants. Most UNDE systems send acoustic pulses into the structure of interest, measure the received waveform, and use an algorithm to reconstruct the quantity of interest. The most widely used algorithm in UNDE systems is the synthetic aperture focusing technique (SAFT) because it produces acceptable results in real time. A few regularized inversion techniques with linear models have been proposed which can improve on SAFT, but they tend to make simplifying assumptions that do not address how to obtain reconstructions from large real datasets. In this paper, we propose a model-based iterative reconstruction (MBIR) algorithm designed for scanning UNDE systems. To further reduce some of the artifacts in the results, we enhance the forward model to account for the transmitted beam profile, the occurrence of direct arrival signals, and the correlation between scans from adjacent regions. Next, we combine the forward model with a spatially variant prior model to account for the attenuation of deeper regions. We also present an algorithm to jointly reconstruct measurements from large datasets. Finally, using simulated and extensive experimental data, we show MBIR results and demonstrate how we can improve over SAFT as well as existing regularized inversion techniques.**

Index Terms—**Nondestructive evaluation (NDE), ultrasound imaging, ultrasound reconstruction, model-based iterative reconstruction (MBIR), regularized iterative inverse, synthetic aperture focusing technique (SAFT).**

I. Introduction

ONE-SIDED ultrasonic nondestructive evaluation (UNDE) is widely used in many applications to characterize and detect flaws in materials, such as concrete structures in nuclear power plants (NPP), because of its low cost, high penetration, portability, and safety compared with other NDE methods [1]–[3]. A typical one-sided UNDE system consists of a sensor that transmits sound waves into the structures of interest and an array of receivers that measures the reflected signals (see Fig. 1). Such a set up is scanned across a large surface in a rectangular grid pattern and the reflected signals from each position are processed to reconstruct the underlying structure. The ability to easily probe structures that can only be accessed from a single side combined along with the ability of ultrasound signals to penetrate deep into structures make one-sided UNDE a powerful tool for the analysis of structures across a variety of applications [4], [5].

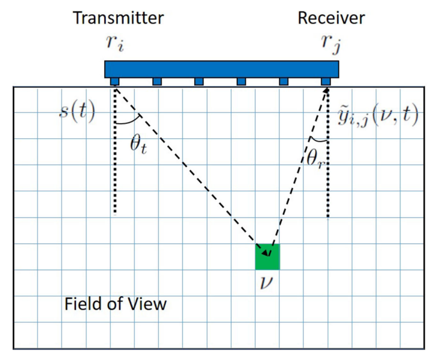

Fig. 1. An illustration of a typical one-sided UNDE problem where $s(t)$ is the transmitted signal, ν is a point in the field-of-view, $y_{i,j}(\nu, t)$ is the received signal reflected from ν, θ_t is the angle between r_i and ν, and θ_r is the angle between r_j and ν.

Reconstruction of structures from one-sided UNDE systems are challenging because of the complex interaction of ultrasound waves with matter, the geometry of the experimental set-up, the trade-off between resolution and penetration, and the potentially low signal-to-noise ratio of the received signals [6], [7]. The most widely used reconstruction method for UNDE is the synthetic aperture focusing technique (SAFT) [4], [8]–[12]. SAFT uses a delay-and-sum (DAS) approach to reconstruct ultrasound images. Fig. 2 shows an example of a SAFT reconstruction from real data. Notice that SAFT reconstructions tend to have significant artifacts due to the fact that SAFT assumes a simple propagation model and does not account for a variety of effects such as noise and image statistics, direct arrival signal artifacts, reverberation, and shadowing [11], [12]. In summary, while SAFT is computationally inexpensive to implement,

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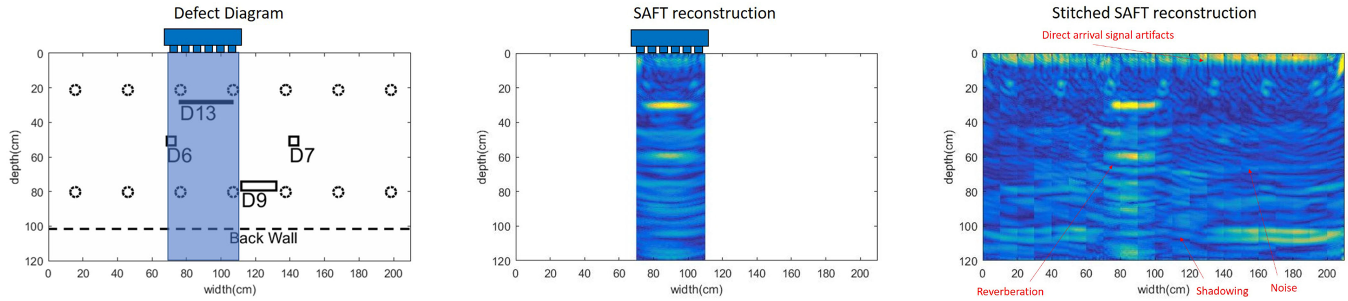


(a) (b) (c)

Fig. 2. Example of a SAFT reconstruction from real data of a concrete structure. (a) The defect diagram containing steel rebars (dotted circles), defects (marked D#), and the back wall (dotted line). (b) SAFT reconstruction for a single scan of the large field-of-view in (a). (c) The SAFT reconstruction for the entire field-of-view after stitching the results from each individual scan.

it can result in significant artifacts in the one-sided UNDE reconstructions.

In order to overcome some of the short-comings of the SAFT method, regularized iterative reconstruction methods that use linear models (due to their low computational complexity) have recently been proposed for various ultrasound inverse problems. These methods formulate the reconstruction as minimizing a cost-function that balances a data fidelity term with a regularization applied to the image/volume to be reconstructed. The data fidelity term encodes a physics based model to reduce the error between the measurements and the projected reconstruction while the regularizer forces certain constraints on the reconstruction itself. For the data fidelity term, regularized iterative techniques for one-sided UNDE, such as [13], [14], use a simple linear model that models the propagation of the ultrasonic wave to reconstruct the reflectance B-mode images. A technique that uses the same forward model, but shows 2D images for a fixed depth (c-mode), is shown in [15]. The forward model in [15] has been upgraded to account for the beam profile as in [16] which can help in reducing some artifacts. However, this forward model does not account for direct arrival signals caused by coupling the ultrasonic device to the surface of the structure which can cause artifacts and interference with reflections. Furthermore, the reconstruction algorithm of [16] is not designed to exploit correlations between adjacent scans for systems with large field-of-view.

In [14], [16]–[18], the authors used a simple regularization terms, such as l_1 or l_2. This regularization is suitable for imaging point scatters or sparse regions. However, for more complex medium where edge preservation is needed, other techniques use a more sophisticated regularization, such as total variation, where they showed significant enhancement over SAFT [13], [15]. The method in [13] uses total variation with variety of a regularization terms that are depth dependent to resolve the attenuation and blurring for deeper reflections. However, the depth-dependent regularization is linear with depth which might not be the best modeling for the depth attenuation. Therefore, while regularized inversion methods that use a linear forward model have shown promise in certain applications, they do not deal with the direct arrival signal artifacts in a principled manner, they have not been designed to jointly handle large data sets that require multiple scanning for one-sided UNDE systems, and they do not fully account for the depth-dependent blurring that can occur by the use of certain regularizers.

In this paper, we propose an ultrasonic model-based iterative reconstruction (MBIR) algorithm designed specifically for one-sided UNDE systems of large structures. We resolve the issues discussed above by enhancing the forward and prior models used in the current regularized iterative techniques. The enhancements to the forward model include a direct arrival signal model with varying acoustic speed and an anisotropic model of the transmitted signal propagation to reduce artifacts in the reconstruction. Also, we repopulate the system matrix of the forward model to generate a larger system matrix for larger field of views to share more information about adjacent scans which can help in reducing noise and artifacts and enhancing the reconstruction. Furthermore, the prior model is enhanced by increasing and conveniently controlling the regularization for deeper regions to reduce the attenuation to these regions. In previous work, we have demonstrated the performance of MBIR compared with SAFT using different combinations of these enhancements [19]–[21]. We introduce four major contributions in this paper:

1) A physics-based linear forward model that models the direct arrival signal with varying acoustic speed, absorption attenuation, and anisotropic propagation;
2) A non-linear spatially-variant regularization to enhance the reconstruction for deeper regions;
3) A systematic way to reconstruct the volume from all the measured data simultaneously rather than individual reconstruction using joint-MAP stitching and 2.5D MBIR;
4) Qualitative and quantitative results from simulated and extensive experimental data.

The paper is organized as follows. In Section II we cover the design for the forward model of the ultrasonic MBIR for one-sided NDE applications. In Section III we cover the prior model used for MBIR. In Section IV we cover the optimization of the MAP cost function using the ICD method. In Section V we cover simulated and experimental results from MBIR and other techniques. In Section VI we cover the conclusion.

II. Forward Model of One-Sided UNDE

The reconstruction in an MBIR setting is given by the following minimization problem,

$$x_{MAP} = \underset{(x)}{\arg\min} \left\{ -\log p(y|x) - \log p(x) \right\},$$

where x is the image to be reconstructed, y is the measured data, x_{MAP} is the reconstructed image, $p(y|x)$ is the forward model and the probability distribution of y given x, $p(x)$ is the prior model and the probability distribution of x. The forward model is designed in the following way. We will consider a one-sided UNDE for a concrete structure where the transducers are coupled to the surface as shown in Fig. 1. We will consider a pressure signal (Pascal) transmitted from transducer i located at position $r_i \in \mathbb{R}^3$, reflected by a point located at $\nu \in \mathbb{R}^3$, and received by transducer j located at $r_j \in \mathbb{R}^3$. We assume the Fourier transform of the temporal impulse response of a system sending a signal from r_i and receiving from ν to be

$$G(r_i, \nu, f) = \lambda e^{-(\alpha(f) + j\beta(f))\|\nu - r_i\|}$$

where λ is a transmittance coefficient,

$$\alpha(f) = \alpha_0 |f| \qquad (\mathrm{m}^{-1})$$

is the rate of attenuation,

$$\beta(f) = \frac{2\pi f}{c} \qquad (\mathrm{m}^{-1})$$

is the phase delay due to propagation through the specimen, and c is the speed of sound [22]–[28]. Similarly, we assume the Fourier transform of the impulse response of a system sending a signal from ν and receiving from r_j to be

$$G(\nu, r_j, f) = \lambda e^{-(\alpha(f) + j\beta(f))\|r_j - \nu\|} .$$

Assuming $s(t)$ (Pascal) is the input to the system and $\tilde{x}(\nu)$ (m^{-3}) is the reflectivity coefficient for ν, then the output $\tilde{Y}_{i,j}(\nu, f)$ (Pascal $\cdot$ m^{-3} $\cdot$ Hz^{-1}) at the receiver due to ν is

$$\begin{aligned} \tilde{Y}_{i,j}(\nu, f) &= -S(f) G(r_i, \nu, f) \tilde{x}(\nu) G(\nu, r_j, f) \\ &= -\lambda^2 \tilde{x}(\nu) S(f) e^{-(\alpha_0 c |f| + j 2\pi f)\tau_{i,j}(\nu)}, \end{aligned}$$

where

$$\tau_{i,j}(\nu) = \frac{\|\nu - r_i\| + \|\nu - r_j\|}{c} \qquad (\mathrm{s}).$$

By defining

$$\tilde{h}(\tau_{i,j}(\nu), t) = \mathcal{F}^{-1} \left\{ -\lambda^2 S(f) e^{-\alpha_0 c |f| \tau_{i,j}(\nu)} \right\}, \qquad (1)$$

where $\mathcal{F}^{-1}$ is the inverse Fourier transform, the time domain output signal, $\tilde{y}_{i,j}(\nu, t)$ (Pascal $\cdot$ m^{-3}), is given by

$$\tilde{y}_{i,j}(\nu, t) = \tilde{h}(\tau_{i,j}(\nu), t - \tau_{i,j}(\nu))\, \tilde{x}(\nu).$$

Note that $\tilde{h}(\tau_{i,j}(\nu), t)$ is a function of $\tau_{i,j}$ and t, i.e., not directly a function of ν. This is a very useful property that can reduce the computational cost of evaluating $\tilde{h}$. In many cases, $\tilde{h}(\tau, t)$ for any τ is close to zero after a certain time t_0. In this case, it is very helpful to modify the previous equation to

$$\tilde{y}_{i,j}(\nu, t) = h(\tau_{i,j}(\nu), t - \tau_{i,j}(\nu))\, \tilde{x}(\nu).$$

where

$$h(\tau, t) = \tilde{h}(\tau, t) \,\mathrm{rect}\left(\frac{t}{t_0} - \frac{1}{2}\right),$$

$$\mathrm{rect}(x) = 1 \text{ for } |x| < \frac{1}{2} \text{ and } 0 \text{ for } |x| \geq \frac{1}{2},$$

and t_0 is a constant where we assume $h(\tau, t)$ is equal to zero for $t > t_0$. Applying the rect function is very helpful in increasing the sparsity of the system matrix which leads to a dramatic decrease in memory and processing time. To get the overall output $\tilde{y}_{i,j}(t)$ (Pascal) from all points in $\mathbb{R}^3$, we need to integrate over all ν:

$$\tilde{y}_{i,j}(t) = \int_{\mathbb{R}^3} \tilde{y}_{i,j}(\nu, t) d\nu \qquad (2)$$

$$= \int_{\mathbb{R}^3} \tilde{A}_{i,j}(\tau_{i,j}(\nu), t) \tilde{x}(\nu) d\nu , \qquad (3)$$

where

$$\tilde{A}_{i,j}(\tau_{i,j}(\nu), t) = h(\tau_{i,j}(\nu), t - \tau_{i,j}(\nu)). \qquad (4)$$

For simplicity, the set of all transducer pairs, $\{i, j\}$, is mapped to the ordered set $\{1, ..., K\}$, where K is the total number of transducer pairs. Hence, Eq. (3) becomes

$$\tilde{y}_k(t) = \int_{\mathbb{R}^3} \tilde{A}_k(\tau_k(\nu), t) \tilde{x}(\nu) d\nu . \qquad (5)$$

Finally, we assume the noise associated with the measurements to be i.i.d. Gaussian.

A. Direct Arrival Signal Artifacts

When the ultrasonic device is attached or coupled to the surface of the concrete, a direct arrival signal is generated along with the transmitted signal. This direct arrival signal produces artifacts on the reconstructed image in regions closer to the transducer and it might interfere with some of the reflected signals (see Fig. 2). Eq. (5) models the output from the reflection of all points. However, the equation does not account for the direct arrival signal. Locating and deleting the direct arrival signal from the received signal eliminates the artifacts, but might lead to deleting reflection signals for closer objects. We propose a modification to the forward model that models the direct arrival signal and attenuates the artifact while preserving information from reflected signals. The modification adds the following term to the forward model in Eq. (5) that corresponds to the direct arrival signal,

$$\tilde{y}_k(t) = \int_{\mathbb{R}^3} \tilde{A}_k(\tau_k(\nu), t) \tilde{x}(\nu) d\nu + \tilde{d}_k(t)\, g_k, \qquad (6)$$

where $\tilde{d}_k(t)$ is an additional term used to model the direct arrival signal given by

$$\tilde{d}_k(t) = -\tilde{A}_k(\tau_k, t),$$

$$\tau_k = \frac{\|r_i - r_j\|}{c},$$

and g_k is an unknown scaling coefficient for the direct arrival signal.

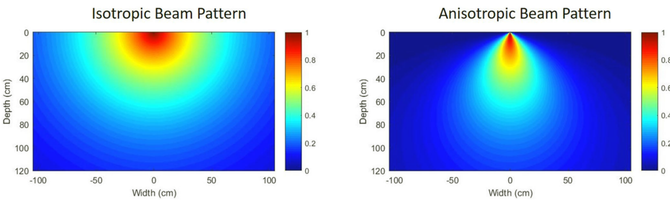


Fig. 3. Beam pattern model for an ultrasound transducer placed at (0, 0) for isotropic propagation (left) and anisotropic propagation (right). Left image shows equal propagation in all direction. Right image shows more attenuation as the angle between the transmitter and the pixel increases.

The above model works efficiently when the acoustic speed is constant. For a non-homogeneous material, such as concrete, the acoustic speed is not constant. This change in acoustic speed changes the location of the direct arrival signal and causes a mismatch with MBIR's direct arrival signal modeling. We can estimate the shift error by searching for the delay that produces the maximum autocorrelation of the direct arrival signal,

$$\hat{l} = \underset{-\tilde{\tau} \le l \le \tilde{\tau}}{\arg\max} \left\{ \int \tilde{y}_k(t) \tilde{d}_k(t-l) dt \right\}$$

$$\tilde{d}_k(t) \leftarrow \tilde{d}_k(t-\hat{l}),$$

where $\tilde{\tau}$ is chosen to be small, e.g., 3 sampling periods, to insure the shift is within the integral boundaries and to avoid interfering with later reflections. This estimate finds the shift error with the assumption that reflections do not interfere with the direct arrival signal. Therefore, for homogeneous medium, our approach is able to reduce direct arrival signal artifacts and detect reflections close to the transducers. However, for non-homogonous medium, our approach is able to reduce direct arrival signal artifacts that do not interfere with reflections.

B. Anisotropic Propagation

Many models used in UNDE assume that the profile of the transmitted beam is isotropic [15], [29]. However, this assumption is not valid for many systems and it can produce artifacts. While it would be ideal to know the precise profile especially of the transmitted beam, in systems that we deal with, this is not known. Therefore, we adopt a similar apodization function as in [4] for the anisotropic model. However, the apodization function used in [4] has a slow attenuating window. In our application, a faster attenuating window is needed. We use an anisotropic beam pattern model as shown in Fig. 3. We define a function, $\phi_k(\nu)$, that has a value ranging from 0 to 1. This function depends on the angles from the transmitter to ν and from ν to the receiver. $\phi_k(\nu)$ is monotonically decreasing with respect to those two angles. $\phi_k(\nu)$ can act as an attenuating window, such as cosine or Gaussian windows, to the output. The function $\phi_k(\nu)$ is added to Eq. (4) as follows:

$$\tilde{A}_k(\tau_k(\nu), t) = h(\tau_k(\nu), t - \tau_k(\nu))\phi_k(\nu). \quad (7)$$

Note that the beam pattern is assumed to be reciprocal, i.e., the receiver will also have the same beam pattern. In this paper, we chose $\phi_k(\nu)$ to be

$$\phi_k(\nu) = \cos^2(\theta_t(\nu)) \cos^2(\theta_r(\nu)) \ ,$$

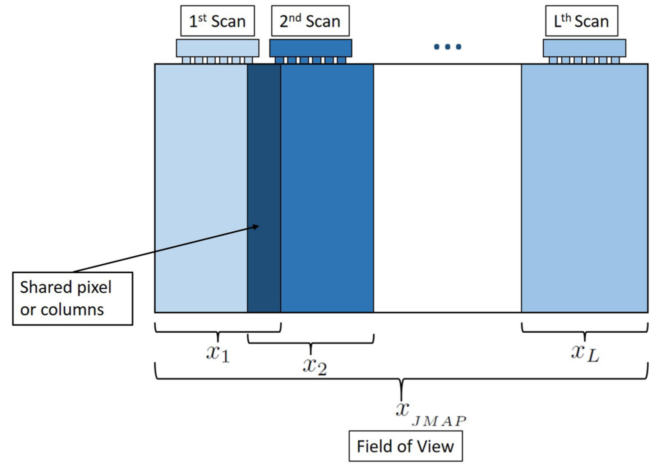


Fig. 4. An illustration of multiple measurements needed to scan a large field-of-view. Images from each scan share some pixels with its neighbor images. Proper stitching technique is needed to account for this shared areas in the field-of-view.

where θ_t is the angle between the transmitter and ν and θ_r is the angle between the receiver and ν shown in Fig. 1.

Finally, the discretized version of the forward model can be used in the MAP estimate as shown below,

$$-\log p(y|x) = \frac{1}{2\sigma^2} \|y - Ax - Dg\|^2 + \text{constant},$$

where $y \in \mathbb{R}^{MK\times 1}$ is the measurement, σ^2 is the variance of the measurement, $A \in \mathbb{R}^{MK\times N}$ is the forward model (system matrix), $x \in \mathbb{R}^{N\times 1}$ is the image, $D \in \mathbb{R}^{MK\times K}$ is the direct arrival signal modeling matrix, $g \in \mathbb{R}^{K\times 1}$ is a vector containing scaling coefficients for the direct arrival signals, M is the number of measurement samples, and N is the number of pixels. The columns of D, d_k, are the discretized version of $\tilde{d}_k$. The vector g is used to scale each column of D independently.

C. Joint-MAP Stitching

In order to scan large regions, the sensor assembly is typically moved from one region to another on the surface in raster order to build up a 3D profile of the structure. Typically each scan is individually processed and placed together to present the overall 3D reconstruction, Fig. 4. However, this method results in sharp discontinuities at the boundaries and inefficient use of the data collected, Fig. 2. We design a joint-MAP technique to solve these issues by modifying the forward model to perform the stitching internally as part of the estimation. This technique is able to remove discontinuities between the sections and make use of any additional information from adjacent scans. Furthermore, the system matrix used in the proposed joint-MAP technique is designed to arrange the small system matrices of single scans in an efficient way to increase the sparsity and reduce the required memory. We assume that adjacent scans share some columns of pixels and have some useful correlations that can be exploited to produce better images. Therefore, the forward model will account for those shared columns differently than the rest of the pixels or columns. For L measurements, we let the system matrix for each measurement be A and the image for each measurement be x_l. We let the order of the pixels in x_l be from top to bottom for each column starting from the far left column to the far right column. Hence, the term associated with the modified forward model in the MAP estimate will be

$$\frac{1}{2\sigma^2}\left\|y_{_{JMAP}} - A_{_{JMAP}} x_{_{JMAP}} - D_{_{JMAP}} g_{_{JMAP}}\right\|^2, \quad (8)$$

where

$$A_{_{JMAP}} = \begin{bmatrix} [\ A\ ] & 0 & 0 & \dots \\ 0 & [\ A\ ] & 0 & \dots \\ 0 & 0 & [\ A\ ] & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix},$$

$$D_{_{JMAP}} = \begin{bmatrix} D & 0 & \dots & 0 \\ 0 & D & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & D \end{bmatrix},$$

$$y_{_{JMAP}} = \begin{bmatrix} y_1 \\ \vdots \\ y_l \\ \vdots \\ y_L \end{bmatrix}, \quad g_{_{JMAP}} = \begin{bmatrix} g_1 \\ \vdots \\ g_l \\ \vdots \\ g_L \end{bmatrix},$$

and $x_{_{JMAP}}$ is the image of the large field-of-view. $A_{_{JMAP}}$ is designed so that if a pixel is shared in more than one image, then its corresponding column in the system matrix for one image will be aligned with its corresponding columns in the system matrix for other images. For the example shown in Fig. 4, we can accomplish this alignment by shifting each system matrix A left or right until the required alignment is achieved.

III. Prior Model of the Image

We design the prior model of the image to be a combination of a Gibbs distribution and an exponential distribution, i.e.,

$$-\log p(x) = \sum_{\{s,r\}\in C} b_{s,r}\ \rho(x_s - x_r, \sigma_g) + \sum_{s\in S} \frac{x_s}{\sigma_e} + \text{constant},$$

where C is the set of all pair-wise cliques, S is the set of all pixels in the field of view, $b_{s,r}$ is a scaling coefficient, ρ is the potential function, σ_g is the regularization constant for the Gibbs distribution, σ_e is the regularization constants for the exponential distribution, and $x_s \geq 0\ \forall s \in S$. We chose the q-generalized Gaussian Markov random field (QGGMRF) as the potential function for the Gibbs distribution [30]. The equation for the QGGMRF is

$$\rho(\Delta, \sigma_g) = \frac{|\Delta|^p}{p\sigma_g^p}\left(\frac{|\frac{\Delta}{T\sigma_g}|^{q-p}}{1+|\frac{\Delta}{T\sigma_g}|^{q-p}}\right), \quad (9)$$

where $1 \leq p < q = 2$ insures convexity and continuity of first and second derivatives, and T controls the edge threshold. The Gibbs distribution is used to preserve edges while the exponential distribution is used to force the background toward zero.

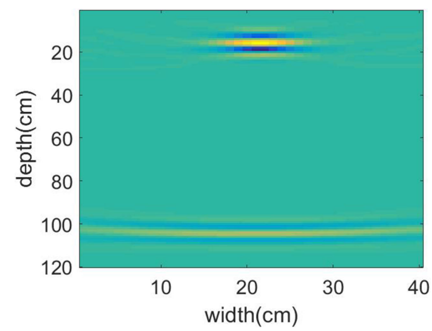


Fig. 5. Back-projection of two point scatters, one that is closer to the transducers (17 cm deep) and one that is far from the transducers (105 cm deep). As the reflection gets deeper, the lateral resolution decreases.

The neighbors of a pixel s are arranged as

$$\begin{bmatrix} r_1 & r_2 & r_3 \\ r_4 & r_5 & r_6 \\ r_7 & r_8 & r_9 \end{bmatrix}, \begin{bmatrix} r_{10} & r_{11} & r_{12} \\ r_{13} & s & r_{14} \\ r_{15} & r_{16} & r_{17} \end{bmatrix}, \begin{bmatrix} r_{18} & r_{19} & r_{20} \\ r_{21} & r_{22} & r_{23} \\ r_{24} & r_{25} & r_{26} \end{bmatrix}. \quad (10)$$

where the neighbors with index 10 to 17 are from the same layer, and the rest of the neighbors are from the next and previous layers. With this arrangement, the scaling coefficients $b_{s,r}$ are chosen to be

$$\begin{bmatrix} b_{s,r_1} & b_{s,r_2} & b_{s,r_3} \\ b_{s,r_4} & b_{s,r_5} & b_{s,r_6} \\ b_{s,r_7} & b_{s,r_8} & b_{s,r_9} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \cdot \frac{\gamma}{4\gamma+12},$$

$$\begin{bmatrix} b_{s,r_{10}} & b_{s,r_{11}} & b_{s,r_{12}} \\ b_{s,r_{13}} & 0 & b_{s,r_{14}} \\ b_{s,r_{15}} & b_{s,r_{16}} & b_{s,r_{17}} \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 0 & 2 \\ 1 & 2 & 1 \end{bmatrix} \cdot \frac{1}{4\gamma+12},$$

$$\begin{bmatrix} b_{s,r_{18}} & b_{s,r_{19}} & b_{s,r_{20}} \\ b_{s,r_{21}} & b_{s,r_{22}} & b_{s,r_{23}} \\ b_{s,r_{24}} & b_{s,r_{25}} & b_{s,r_{26}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \cdot \frac{\gamma}{4\gamma+12},$$

with a free boundary condition. The parameter γ is set to zero when 2D MBIR is needed, or greater than zero when a 3D regularization (2.5D MBIR) is needed. 2.5D MBIR can be used to gain more information from neighbors of different layers to reduce noise and increase resolution.

A. Non-Linear Spatially-Variant Regularization

The standard form of the regularization introduced above uses constant σ_g and σ_e for all voxels. This can result in reconstruction artifacts because there are few pixels that could have contributed to the signal for closer reflections. However, for deeper reflections, there are many more pixels that could have caused the reflection, i.e., the deeper the reflection the less lateral resolution it has. Fig. 5 shows the back-projection of two point scatters of different depth. The closer reflection has less overlapping and higher lateral resolution. The deeper reflection has larger overlapping and lower lateral resolution. This is an issue because MBIR spreads the energy over the intersection area, which attenuates the intensity dramatically for deeper reflections. This smoothing and attenuation appear to increase more rapidly for deeper reflection. Therefore, a linear spatially-variant regularization as in [13] is not sufficient, and a more generalized model is needed. Hence, we adapt a non-linear spatially-variant regularization technique designed for the UNDE system. We can solve the attenuation problem by assigning less regularization as the pixel gets deeper. The disadvantage of this method is that it will amplify both the reflection and the noise for deeper pixels.

We replace σ_g and σ_e with $\sigma_{g_{s,r}}$ and σ_{e_s}, respectively, where these new parameters are monotone increasing with respect to depth. We assign a new scaling parameter c_s that varies between two values, 1 and $c_{\max}$, as follows:

$$c_s = 1 + (c_{\max} - 1) * \left(\frac{\text{depth of pixel } s}{\text{maximum depth}}\right)^a \tag{11}$$

where $a > 0$ and $c_{\max} > 1$. Then, $\sigma_{g_{s,r}}$ and σ_{e_s} are calculated as follows:

$$\sigma_{g_{s,r}} = \sigma_g \sqrt{c_s c_r},$$
$$\sigma_{e_s} = \sigma_e c_s \ ,$$

where c_r has the same equation as in c_s, but for pixel r.

B. Selection of Prior Model Parameters

The selection of the prior model parameters is an open area of research. In this paper, we select the regularization parameters σ_g, σ_e and γ (which control edge preservation, background sparsity, and contribution from neighbors of adjacent layers, respectively) to produce the best results visually. The parameters p, q, T, and a (which controls the transitioning from high to low regularization as the pixels get deeper) are unitless parameters and the values used for them in this paper are considered standard and seem to be consistent with the applications we are working on. The parameter $c_{\max}$ is a unitless parameter and is used to amplify reflections for deeper regions as needed.

IV. Optimization of MAP Cost Function

After designing the forward model and the prior model, the MAP estimate becomes

$$\begin{aligned}(x, g, \sigma^2)_{MAP} = \underset{x\geq 0, g, \sigma^2}{\arg\min} \Bigg\{ &\frac{1}{2\sigma^2} \|y - Ax - Dg\|^2 \\ &+ \frac{MK}{2} \log(\sigma^2) + \sum_{\{s,r\}\in C} b_{s,r}\ \rho(x_s - x_r, \sigma_{g_{s,r}}) \\ &+ \sum_{s\in S} \frac{x_s}{\sigma_{e_s}} \Bigg\}.\end{aligned} \tag{12}$$

The shifting of the direct arrival signal matrix D mentioned in Section II-A is performed once before estimating g, x and σ^2. The solution for g is straightforward:

$$\begin{aligned}0 = &\ \nabla_g \Bigg\{ \frac{1}{2\sigma^2} \|y - Ax - Dg\|^2 + \frac{MK}{2} \log(\sigma^2) \\ &+ \sum_{\{s,r\}\in C} b_{s,r}\ \rho(x_s - x_r, \sigma_{g_{s,r}}) + \sum_{s\in S} \frac{x_s}{\sigma_{e_s}} \Bigg\} \\ \Rightarrow &\ 0 = 2D^t Dg + 2D^t Ax - 2D^t y \\ \Rightarrow &\ g = (D^t D)^{-1} D^t (y - Ax).\end{aligned}$$

Given x, the evaluation of g is computationally inexpensive because $D^t D$ is a diagonal matrix, i.e.,

$$(D^t D) = \begin{bmatrix} d_1^t d_1 & 0 & \dots & 0 \\ 0 & d_2^t d_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & d_K^t d_K \end{bmatrix},$$

where d_k is the discretized version of $\tilde{d}_k(t)$ for transducer pair k. However, g requires the knowledge of x which is the image we would like to reconstruct. This issue can be resolved by updating the value of g from the updated image in each iteration. Furthermore, for each iteration, we update g, x, and σ^2 in the following steps:

$$\begin{aligned} g &\leftarrow (D^t D)^{-1} D^t (y - Ax) \\ y &\leftarrow y - Dg \\ x &\leftarrow \underset{x\geq 0}{\arg\min} \Big\{ -\log p(y|x) - \log p(x) \Big\} \\ \sigma^2 &\leftarrow \frac{1}{MK} \|y - Ax\|^2 \end{aligned}$$

We adopt the iterative coordinate descent (ICD) technique to optimize the cost function with respect to x [31]. Since the prior model term is non-quadratic, optimizing the cost function will be computationally expensive. Therefore, we use the surrogate function (majorization) approach with ICD to resolve this issue [30]. This ICD optimization algorithm is guaranteed to converge to the global minimum because the function being minimized is continuously differentiable and strictly convex [30]. Fig. 6 shows the complete algorithm for ICD using the majorization approach. The algorithm is stopped either if

$$\frac{\|x_{n-1} - x_n\|}{\|x_{n-1}\|} < \epsilon, \tag{13}$$

where x_n is the current image update and ϵ is a stopping threshold, or if the number of iterations exceeds a specified number, e.g., 100 iterations. Empirically, we have found that a value of $\epsilon = 0.01$ is a sufficient value to declare convergence with zero initialization.

V. Results

In this section we compare MBIR with two different techniques qualitatively and quantitatively.

ICD Algorithm Using Majorization Technique

Initialize $x,\ e \leftarrow y - Ax,\ \sigma^2$

For $p = 1$: Number of transducer pairs{

$n_p = \arg\max_{n_p}\{y_p^t d_p(n - n_p)\}$

$d_p \leftarrow d_p(n - n_p)$

}

Repeat if stopping condition is not met {

$g = (d^t d)^{-1} d^t e$

$e \leftarrow e - dg$

For each pixel $s \in S${

$\tilde{b}_{s,r} \leftarrow \frac{b_{s,r}\rho'(x_s - s_r)}{2(x_s - x_r)}$

$\theta_1 \leftarrow -\frac{e^t A_{*,s}}{\sigma^2} + \sum_{r\in\partial s} 2\tilde{b}_{s,r}(x_s - x_r)$

$\theta_2 \leftarrow \frac{A_{*,s}^t A_{*,s}}{\sigma^2} + \sum_{r\in\partial s} 2\tilde{b}_{s,r}$

$\alpha^* \leftarrow \text{clip}\left\{\frac{-\theta_1}{\theta_2}, [-x_s, \infty)\right\}$

$e \leftarrow e - A_{*,s}\alpha^*$

$x_s \leftarrow x_s + \alpha^*$

}

$\sigma^2 \leftarrow \frac{\|e\|^2}{MK}$

}

Fig. 6. ICD algorithm using the majorization technique with shift error estimation (top red box) and direct arrival modeling (bottom red box) [30], [31].

A. Algorithms for Comparison

We compare MBIR with the SAFT and l_1-norm techniques. The l_1-norm is a regularized iterative technique with the same forward model as in Eq. (5) with an exponential distribution prior. The prior model is exactly equal to an l_1 regularization term with a positivity constraint. The MAP estimate for the l_1-norm technique is

$$(x, \sigma^2)_{MAP} = \arg\min_{x\geq 0, \sigma^2}\left\{\frac{1}{2\sigma^2}\|y - Ax\|^2 + \frac{MK}{2}\log(\sigma^2) + \sum_{s\in S}\frac{x_s}{\sigma_{e_s}}\right\}. \quad (14)$$

A pixel-wise precision-recall (PR) plot is used for the simulated data to compare the performance of the techniques qualitatively. A pixel-wise PR test calculates the number of true positive (TP), false positive (FP), and false negative (FN) for each technique. These values are used to plot the precision vs. recall (PR) curves where

$$\text{recall} = \frac{TP}{TP + FN}$$

and

$$\text{precision} = \frac{TP}{TP + FP}.$$

This detection test compares the performance of each technique by the area under the PR curve. The larger the area the better the technique. Next, for each technique, all the images are normalized by dividing them with their maximum value. Thresholds from 1 to 0 with step 0.001 are applied to all images. For each threshold, a TP is declared if the defect diagram (ground truth) pixel is 1 and the reconstructed pixel is 1. A FP is declared if the defect diagram pixel is 0 and the reconstructed pixel is 1. A FN is declared if the defect diagram pixel is 1 and the reconstructed pixel is 0.

The techniques performance for the simulated data will be compared with measurements of different signal-to-noise ratio (SNR). The SNR is defined as

$$SNR = \frac{\|y\|^2}{\|w\|^2},$$

where y is the noiseless simulated output from k-wave, and w is the added noise to y.

A component-wise PR plot is used for the experimental data to compare the performance of each technique. Each image is segmented into connected components using the standard Matlab functions "edge" and "imfill". Next, the maximum value and weighted centroid for each connected component is stored. Next, a search is performed pairing targets from the defect diagram to connected components from the reconstruction in the following way: A connected component is mapped to a particular target if its centroid is both the closest among all detected components to the target's centroid, and it is within 10 cm of the target's centroid. Next, for each technique, all the images are normalized by dividing them with the maximum value of them all. Thresholds from 1 to 0 with step 0.001 are applied to all images. For each threshold, a TP is declared if the maximum value of a paired connected component is equal or greater than the threshold. A FP is declared if the maximum value of an unpaired connected component is equal or greater than the threshold. The FN is calculated by subtracting the number of TP's from the number of targets.

A normalized root mean square error (NRMSE) plot will be used to compare MBIR convergence with different initializations. The NRMSE is defined as

$$NRMSE(n) = \frac{\|X_n - X_{true}\|}{\|X_{true}\|}, \quad (15)$$

where n is the iteration number, and X_{true} is the true solution. We define X_{true} to be iteration 1500 of the zero initialization.

B. K-Wave Simulated Results

The k-wave simulator has been used to simulate acoustic propagation through concrete medium [32]. The concrete structure was embedded with steel of different shapes. The width and depth of the structure is 40 cm and 30 cm , respectively. 10 transducers were used to transmit and receive. For each simulation, the simulator produces 90 outputs from all pairs of transducers where only distinct pairs are used, i.e., 45 distinct pairs. The transducers are placed at the top center of the field-of-view and separated by 4 cm from each other. To simulate the acoustic propagation using k-wave, we provided three images of speed, density, and attenuation as inputs to k-wave. Each pixel in the three input images corresponds to the characteristics of either steel or cement. The output of k-wave is then used as input to the reconstruction methods. Fig. 7 shows reconstruction results for four different tests. The voxel spacing for 2D reconstructions is 1 cm for all reconstruction techniques. The left column shows

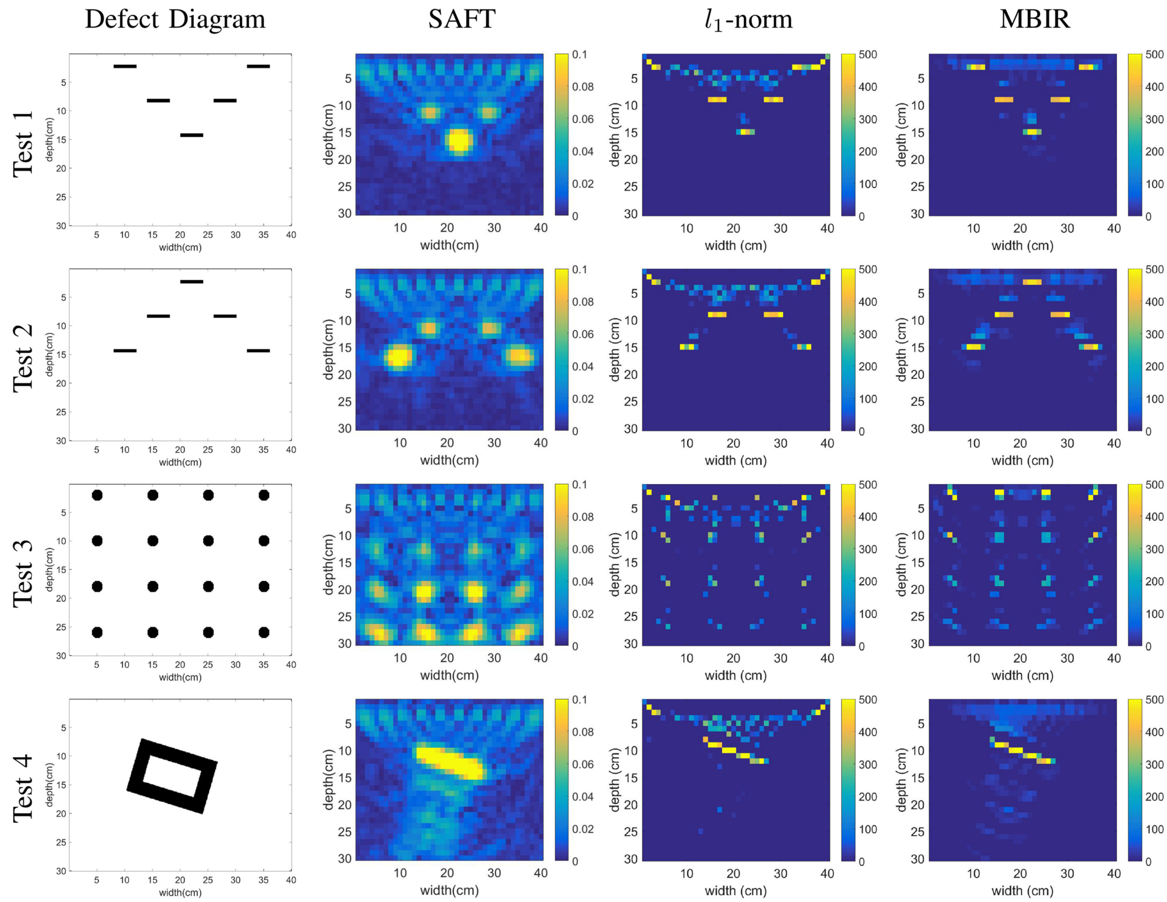


Fig. 7. Comparison between MBIR and SAFT reconstruction from the k-wave simulated data. The far left column is the position of the defects. The next column is SAFT reconstruction. The next column is l_1-norm reconstruction. The far right column is MBIR reconstruction. MBIR tends to produce results with less noise and artifacts compared to SAFT and l_1-norm.

TABLE I
PARAMETER SETTINGS FOR K-WAVE SIMULATION

Parameters	Value	Unit
Carrier frequency	52	kHz
Sampling frequency	1	MHz
Cement speed	3680	m/s
Cement density	1970	Kg/m^3
Cement attenuation	1.46e-6	$dB/((MHz)^y cm)$
Steel speed	5660	m/s
Steel density	8027	Kg/m^3
Steel attenuation	4.85e-8	$dB/((MHz)^y cm)$
Spatial resolution	1	mm
Number of columns	400	-
Number of rows	300	-
Number of transducers	10	-

TABLE II
PARAMETER SETTINGS USED FOR ALL TECHNIQUES TO RECONSTRUCT THE EXPERIMENTAL MIRA DATA

Parameters	Value	Unit
Carrier frequency	52	kHz
Sampling frequency	200	kHz
Cement p-wave speed	2620	m/s
Reconstruction resolution	1	cm
Number of columns	210	-
Number of rows	120	-

the designed defect diagram that was used for simulation where the white pixels corresponds to cement and the black pixels corresponds to steel. The next column shows the instantaneous envelope of SAFT reconstruction. The next column is l_1-norm. The right column shows the MBIR reconstruction. Both l_1-norm and MBIR were initialized to zero. Note that SAFT does not share the same unit with MBIR or L1-norm. That is why it shows different scaling.

Fig. 9 shows the pixel-wise PR curve for each technique over all 4 tests. Table IV shows values of the area under the PR curves in Fig. 9. Table I shows the parameters which are used for k-wave simulation, and some of them are used as input parameters in all techniques. Table III shows the parameters used for l_1-norm and MBIR in Eq. (1), (9), and (11), and the stopping threshold.

Fig. 8 shows a comparison between the methods with noise added to the simulated signal of the defect diagram of Test 1 in Fig. 7.

Discussion: In Fig. 7, MBIR and l_1-norm were able to show significant enhancement over SAFT in reducing noise. MBIR showed remarkable performance in identifying, eliminating, and distinguishing the direct arrival signal artifacts from the steel

TABLE III
THE l_1-NORM, 2D MBIR, AND 2.5D MBIR PARAMETER SETTINGS USED IN THE SIMULATED K-WAVE AND THE EXPERIMENTAL MIRA DATA

Parameters	l_1-norm	2D MBIR	2.5D MBIR	Unit
ϵ	0.01	0.01	0.01	-
α_0	30	30	30	$(MHz \cdot m)^{-1}$
p	-	1.1	1.1	-
q	-	2	2	-
T	-	1	1	-
c_{max}	-	10	10	-
a	-	3	3	-
σ_g	-	3	3	m^{-3}
σ_e	15	15	15	m^{-3}
γ	-	-	0.5	-

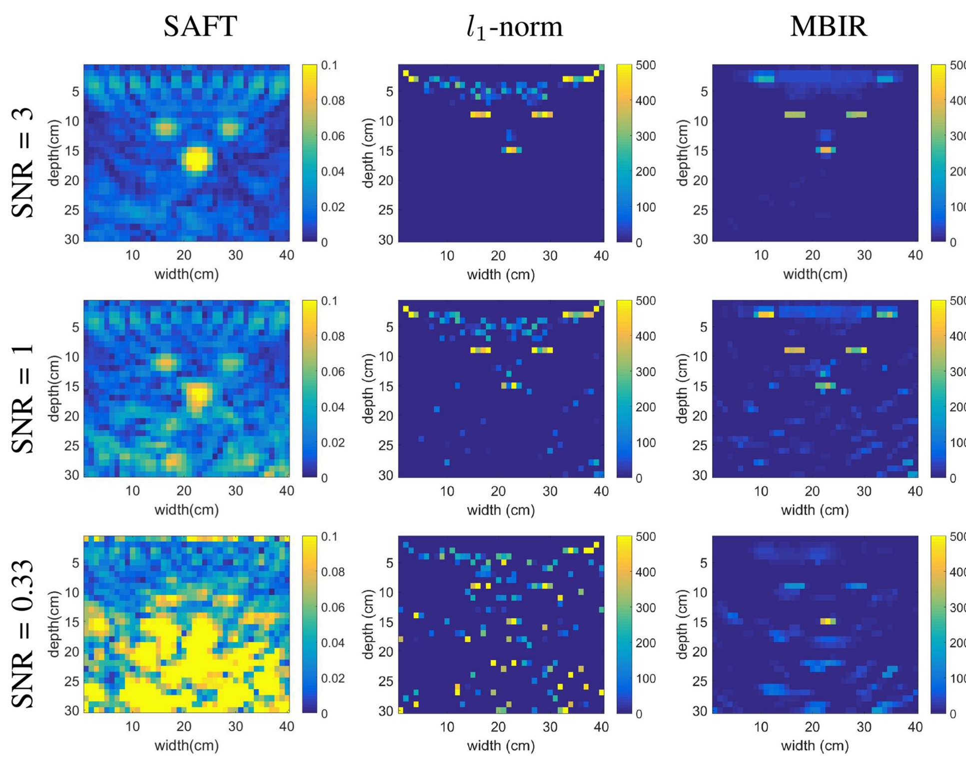


Fig. 8. Comparison between SAFT, l_1-norm, MBIR reconstructions from the k-wave simulated data with different SNR. The defect diagram is the same as the defect diagram in Test 1 in Fig. 7. The left column is SAFT reconstruction. The next column is l_1-norm reconstruction. The right column is MBIR reconstruction. Each row correspond to different SNR value where the SNR values from top to bottom are 3, 1, and 0.33, repectively. MBIR tends to produce results with less noise and artifacts compared to SAFT and l_1-norm.

objects. For example, in test 1, two steel plates where placed at depth 2 cm. The plates where overshadowed by the direct arrival signal artifacts in SAFT and l_1-norm, but appear very clearly in MBIR. Test 2 and 3 also show similar direct arrival signal overshadowing effects for SAFT and l_1-norm, that are reduced for MBIR. In addition, the steel objects are more easily observed and recognized in l_1-norm and MBIR. In Fig. 9 and Table IV, MBIR shows better performance in the detection test with the highest PR area.

Notice that in test 4, none of the techniques were able to show the complete structure of the steel object. They were able to show only one side of it. This is because all three reconstruction methods reconstruct the reflections caused by discontinuous boundaries rather than recovering the actual material property at each voxel location.

Fig. 8 shows the reconstruction of test 1 in Fig. 7 with varying signal-to-noise ratio (SNR). As the SNR decreases, the reconstruction becomes noisier for all techniques. However, the results show better performance in MBIR than the other techniques in reducing noise and artifacts.

C. MIRA Experimental Results

Experimental results have been obtained from a designed thick concrete specimen [33]. The height and width of the specimen is 213.36 cm (84 inches), Fig. 10. The depth of the

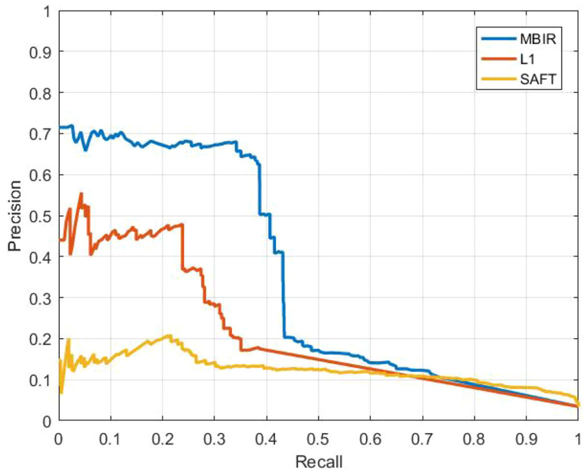


Fig. 9. PR curves for each technique over all 4 tests in Fig. 7. MBIR outperforms the other techniques by having the highest PR area.

TABLE IV
PRECISION VS RECALL AREA FOR ALL TECHNIQUES IN FIG. 9 AND FIG. 17. MBIR HAS THE HIGHEST PR AREA

	SAFT	l_1-norm	2D MBIR	2.5D MBIR
PR area for k-wave data	0.1236	0.2131	0.3476	-
PR area for MIRA data	0.1397	0.1932	0.2836	0.2908

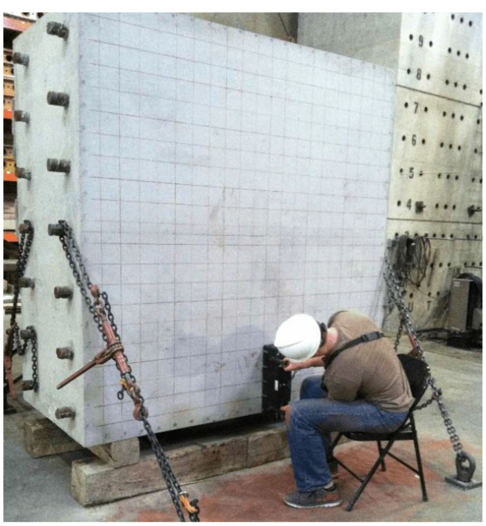
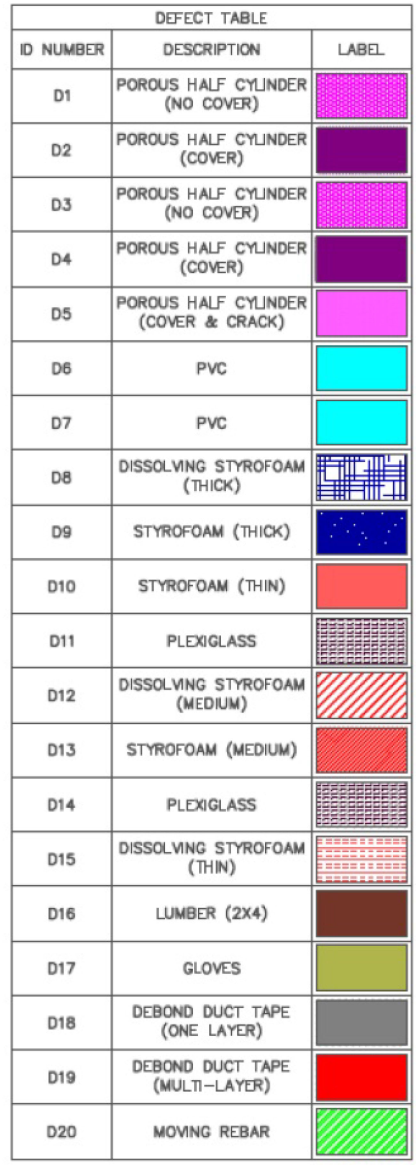


Fig. 10. The concrete specimen used for the experimental data [33]. 20 defects are embedded in the specimen.



DEFECT TABLE		
ID NUMBER	DESCRIPTION	LABEL
D1	POROUS HALF CYLINDER (NO COVER)	
D2	POROUS HALF CYLINDER (COVER)	
D3	POROUS HALF CYLINDER (NO COVER)	
D4	POROUS HALF CYLINDER (COVER)	
D5	POROUS HALF CYLINDER (COVER & CRACK)	
D6	PVC	
D7	PVC	
D8	DISSOLVING STYROFOAM (THICK)	
D9	STYROFOAM (THICK)	
D10	STYROFOAM (THIN)	
D11	PLEXIGLASS	
D12	DISSOLVING STYROFOAM (MEDIUM)	
D13	STYROFOAM (MEDIUM)	
D14	PLEXIGLASS	
D15	DISSOLVING STYROFOAM (THIN)	
D16	LUMBER (2X4)	
D17	GLOVES	
D18	DEBOND DUCT TAPE (ONE LAYER)	
D19	DEBOND DUCT TAPE (MULTI-LAYER)	
D20	MOVING REBAR	

Fig. 11. Type and legend for each defect [33]. These defects are embedded in the concrete specimen.

specimen is 101.6 cm (40 inches). Each side of the block is gridded with 10.16 cm squares producing 21 rows and columns. The specimen has been heavily reinforced with steel rebars horizontally and vertically with 1 ft separation in both sides. One side is "smooth" and the other is "rough" which refer to the physical characteristic of the concrete surface due to pouring. Also, Fig. 12 and Fig. 13 show diagrams of the steel rebars in green color with more details. The specimen has been embedded with designed defects placed in specific locations. The type and location of the defects are shown in Figs. 11, 12, 13, and 14 [33]. The specified location of the defects might be different from the real location due to possible displacement while pouring the cement.

The defects are designed to simulate real defects that can occur due to construction process, cumulative deterioration, or degradation of concrete. Four datasets were obtained by scanning both sides horizontally and vertically: smooth-horizontal, smooth-vertical, rough-horizontal, and rough-vertical. Each dataset contains 17 to 19 cross-sections or slices of the specimen which adds up to 73 cross-sections. Each cross-section is scanned 18 times from different positions to cover the entire field of view. The first and last scans are centered at 20.32 cm (8 inches) from the edge. The rest of the scans are spread evenly by a 10.16-cm (4-inch) separation, hence the 18 scans.

The MIRA system has been used to collect the data, Fig. 15. The MIRA device contains 10 columns or channels separated by 40 mm where each channel contains 4 dry contact points with

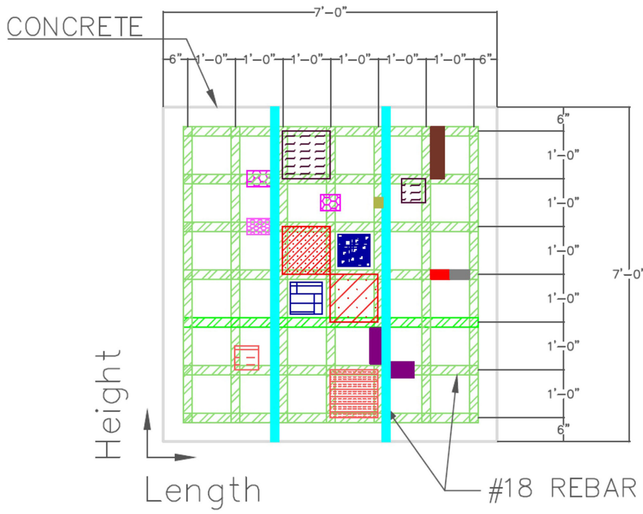


Fig. 12. Smooth side view of defects [33]. The location of the defects is approximated due to possible displacement while pouring the cement.

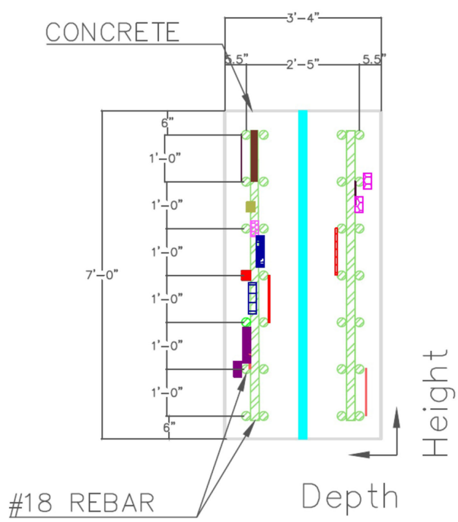


Fig. 13. Depth view of defects, smooth side on the right and rough side on the left, [33]. The location of the defects is approximated due to possible displacement while pouring the cement.

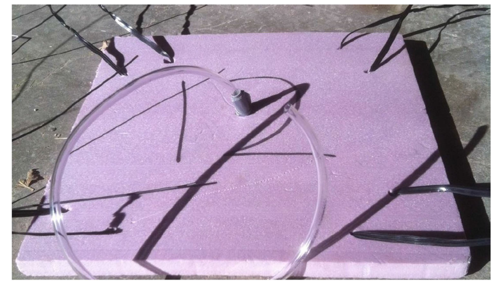


Fig. 14. A picture of defect 12 before embedding it in the specimen, [33]. It is made of dissolving styrofoam.

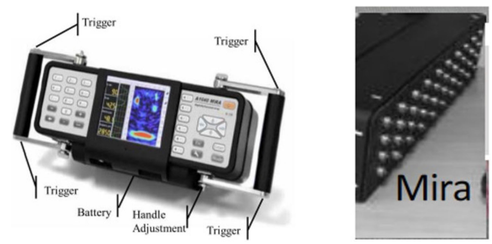


Fig. 15. A picture of the MIRA device used for the experimental data. The device has 10 columns of transducers, where each column acts as a single transducer.

2 mm radius that act as transmitters or receivers. Only the 45 distinct pairs are used in the reconstruction results for all techniques. The transmitter emits a signal with a carrier frequency of 52 kHz, and the sampling frequency of the receiver is 1 MHz. The acoustic speed is assumed to be $2620\frac{m}{s}$. Each distinct pair produces 2048 samples of data where the first 27 samples are ignored due to trigger synchronization. The data is then downsampled to 200 kHz and 409 samples and reconstructed using all techniques.

Four different techniques were used to reconstruct the data: SAFT, l_1-norm, 2D MBIR, and 2.5D MBIR. Zero initialization was used for l_1-norm, 2D MBIR, and 2.5D MBIR.For SAFT, the multiple scans are jointly reconstructed to avoid stitching artifacts. For l_1-norm, all scans for each cross-section are reconstructed individually and then stitched together. For 2D MBIR and 2.5D MBIR, the joint-MAP stitching is used to reconstruct the entire cross-section.

Fig. 16 shows the reconstruction results. The field of view of each cross-section is 120×210 cm and the reconstruction resolution is 1 cm for all techniques. The first row shows the defect diagram and the position of the defects. The second row is the instantaneous envelope of SAFT reconstruction. The third row is l_1-norm reconstruction. The fourth row is 2D MBIR reconstruction. The fifth row is 2.5D MBIR reconstruction. Note that the defect diagram shows the steel rebars as dotted circles or dotted rectangles. The steel rebars might appear in all reconstructions as small horizontal dots or a horizontal line at the top, but the bottom steel rebars barely appear in all techniques due to their weak reflection. Table II shows the common parameter settings for all techniques. Table III shows the l_1-norm and MBIR parameter settings for Eq. (1), (9), and (11), γ in Section III, and the stopping threshold.

Fig. 17 shows the PR curve for each technique over the four datasets. Since the position of the targets in the defect diagram is not precise, the detection test was done using the component wise approach rather than the pixel-wise approach used for the k-wave data. To make a fair comparison, the parameter σ_g for MBIR, the parameter σ_e for l_1-norm, and the parameters σ_g and γ for 2.5D MBIR were chosen using a grid search to maximize the area under the PR curves. Table IV shows the value of the area under the PR curves in Fig. 17.

All the techniques were implemented in Linux using a 2.60 GHz Sky Lake CPU. SAFT, l_1-norm, 2D MBIR, and 2.5D MBIR processed the four datasets which consist of 73 slices of size 120×210 pixels in approximately 1, 28, 23, and 30 minutes, respectively.

Discussion: In Fig. 16, MBIR shows significant enhancement in reducing artifacts and reducing noise compared with SAFT

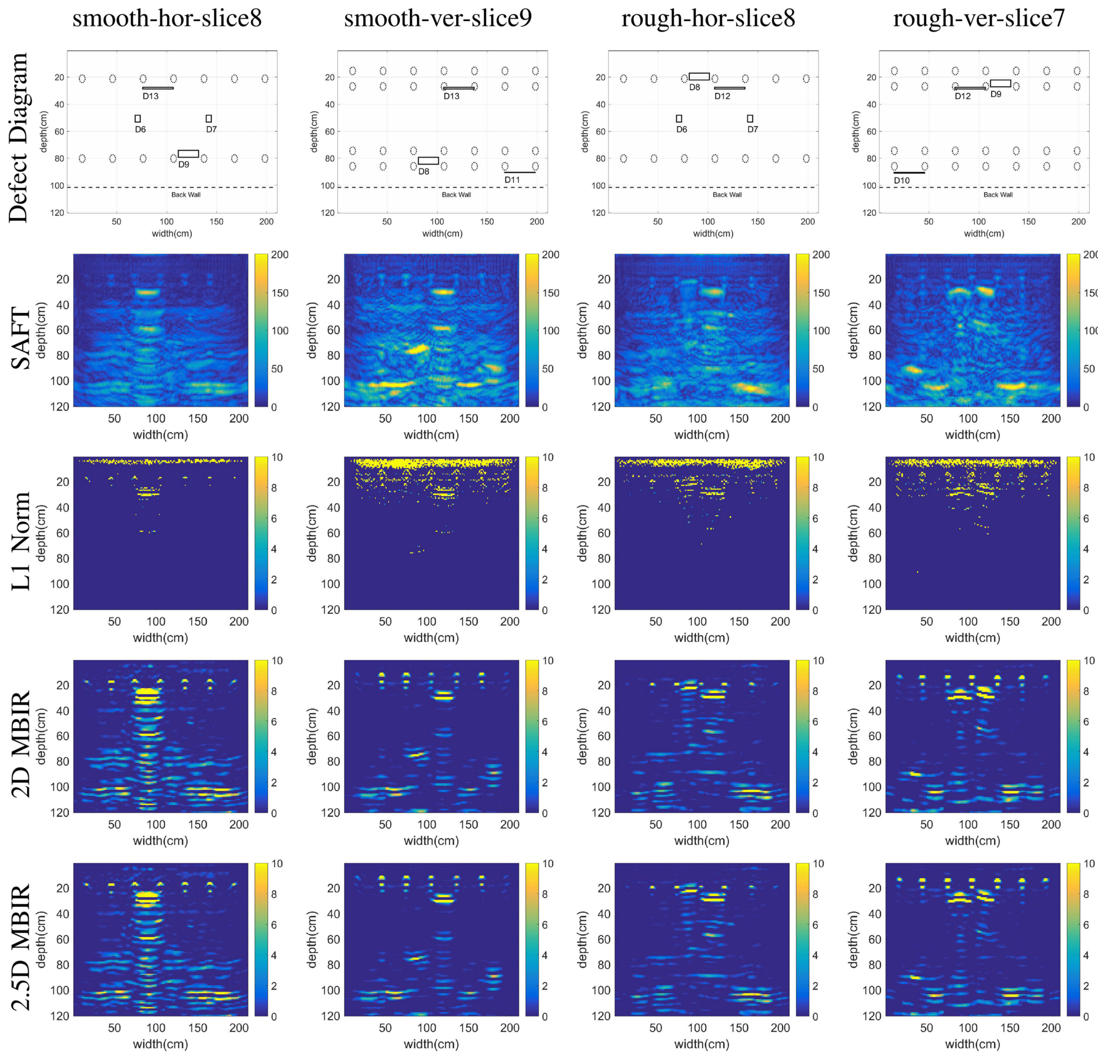


Fig. 16. Comparison between all reconstruction results from the MIRA experimental data: the first row from the top is the position of the defects, the second row is SAFT reconstruction, the third row is l_1-norm reconstruction, the fourth row is 2D MBIR reconstruction, and the fifth row is 2.5D MBIR reconstruction. 2.5D and 2D MBIR tend to produce results with less noise and artifacts compared to other techniques.

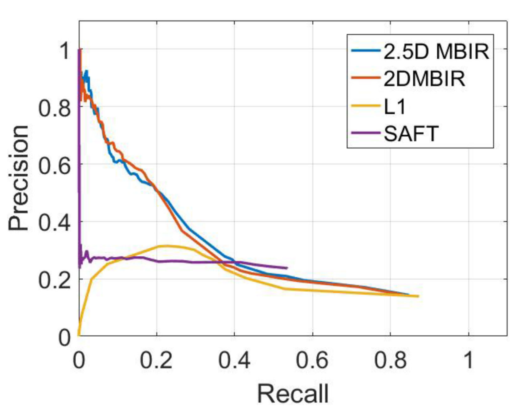


Fig. 17. PR curves for each technique over all 73 slices in the MIRA experimental data. 2.5D and 2D MBIR outperforms the other techniques.

and l_1-norm. SAFT and MBIR techniques were able to show the back wall of the specimen. The back wall is located at depth 100 cm. The detection test showed better performance of 2.5D and 2D MBIR over all techniques with 2.5D MBIR being slightly better than 2D MBIR.

Since all three algorithms are based on a linear forward model, they all exhibit certain reconstruction artifacts such as multiple reflection echos of a single defect. For example, multiple echos appeared of defect 13 in smooth-ver-slice8 for all techniques.

D. Results From Modifying the Forward and Prior Models

In this section, we investigate the effect of various MBIR model attributes on the image quality resulting from the MIRA data reconstructions. In particular, we computed reconstructions *without* direct arrival signal elimination, shift error estimation, anisotropic reconstruction, and spatially variant regularization. We then compared each of these degraded results to the baseline MBIR reconstructions using the complete MBIR algorithm in order to better understand the value of each technique in overall image quality. We also calculated the component-wise PR area for each reconstruction.

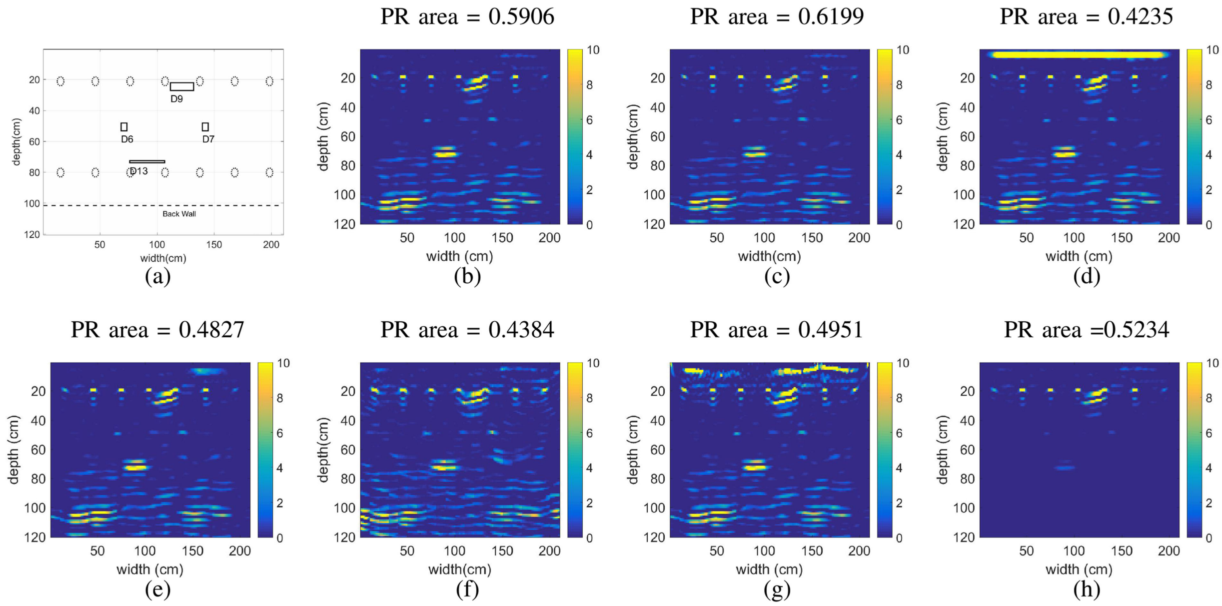


Fig. 18. A comparison between different settings of MBIR where (a) is the defect diagram of rough-hor-slice11, (b) is 2D MBIR reconstruction, (c) is 2.5D MBIR reconstruction with all modifications to the forward and prior models, (d) is 2D MBIR reconstruction without direct arrival signal or shift error estimation, (e) is 2D MBIR reconstruction without shift error estimation, (f) is 2D MBIR reconstruction using regular stitching, (g) is 2D MBIR reconstruction using an isotropic model, and (h) is 2D MBIR reconstruction for a constant regularization. The results in (c) shows performance enhancement over the other results.

Fig. 18 compares MBIR performance when not using each modification. Fig. 18(b) shows 2D MBIR reconstruction with PR area = 0.5906. Fig. 18(c) shows 2.5D MBIR reconstruction with PR area = 0.6199. Fig. 18(d) shows 2D MBIR reconstruction without the direct arrival signal modeling with PR area = 0.4235. Fig. 18(e) shows 2D MBIR reconstruction with the direct arrival signal modeling, but not the shift error estimation, with PR area = 0.4827. Fig. 18(f) shows 2D MBIR reconstruction with regular stitching with PR area = 0.4384. Fig. 18(g) shows 2D MBIR reconstruction with an isotropic forward model with PR area = 0.4951. Fig. 18(h) shows 2D MBIR reconstruction with constant regularization with PR area = 0.5234. All the PR areas specified in Fig. 18 were obtained by calculating the precision and recall for each plot for only the cross-section shown in Fig. 18(a).

Discussion: Fig. 18(d) does not model the direct arrival which causes the reconstruction to have artifacts at the top of the image. These artifacts have high amplitude and could overshadow targets closer to the transducers. Fig. 18(e) reduces these artifacts by modeling the direct arrival signal. However, some residual of the artifacts still appears at the top right corner due to changes in acoustic speed in the concrete medium. Fig. 18(f) shows the results of performing conventional stitching technique to stitch the reconstruction from multiple scans. The stitching method produces vertical discontinuities at the boundaries between the stitched images. Also, the stitching method does not make use of additional information that can be obtained from adjacent scans to improve the reconstruction. Fig. 18(g) uses an isotropic model for the transmitted beam which produces artifacts at the top of the image. These artifacts appear because of the assumption that the signal travels in all directions equally which allows MBIR to use pixels with large transmitter-pixel or pixel-receiver angles to fit the data. Fig. 18(h) uses a spatially constant regularization which suppresses weak details in deep regions of the reconstruction. This results from the fact that the signal is dramatically attenuated as it propagates into deeper regions. Consequently, reconstruction with a constant regularization attenuates most useful detail in the deep parts of the image.

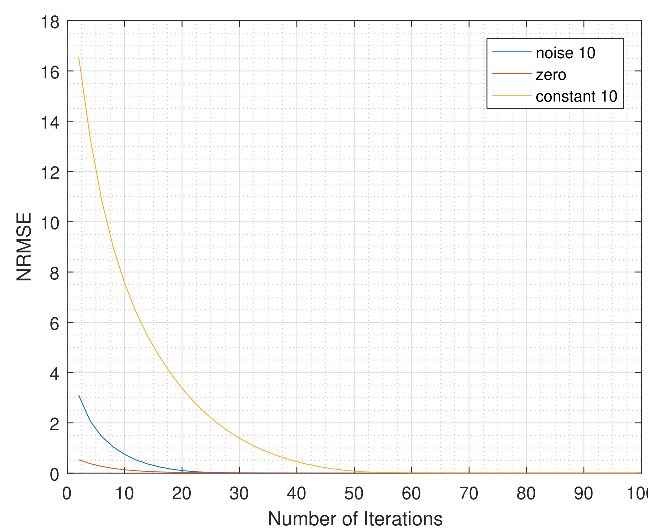


Fig. 19. NRMSE vs. iteration for different initializations in the MBIR algorithm. The initializations used in the plot are uniformly distributed random noise with range [0, 10], zero, and a constant value of 10, respectively.

In contrast, Fig. 18(b) shows 2D MBIR with much better performance in reducing artifacts, exploiting correlations from adjacent scans, showing targets for deeper regions, and having larger PR area. Finally, Fig. 18(c) shows the 2.5D MBIR reconstruction which is qualitatively and quantitatively slightly better than 2D MBIR.

E. Convergence of MBIR

To show the algorithm's convergence behavior, we reconstructed cross-section rough-hor-slice11 in Fig. 18 a from the MIRA data with different initializations: uniformly distributed random noise with range [0, 10], zero, a constant value of 10. Fig. 19 shows the NRMSE vs. iteration for the different initializations.

VI. Conclusion

This paper proposed an MBIR algorithm for ultrasonic one-sided NDE. The paper showed the derivation of a linear forward model. The QGGMRF potential function for the Gibbs distribution prior model was chosen for this problem because it guarantees function convexity, models edges and low contrast regions, and has continuous first and second derivatives. Furthermore, we proposed modifications to both the forward and prior models that improved reconstruction quality. These modifications included direct arrival signal elimination, anisotropic transmit and receive pattern, and spatially variant regularization. Additionally, a joint-MAP estimate and a 2.5D MBIR were performed to process large multiple scans at once which helps reduce noise and artifacts dramatically compared with results from individual scans. The research was supported by simulated and extensive experimental results. The results compared the performance of MBIR with SAFT and l_1-norm qualitatively and quantitatively. The results showed noticeable improvements in MBIR over SAFT and l_1-norm in reducing noise and artifacts.

While the results of this paper are promising, it is worth mentioning the need of a non-linear forward model to address the issues due to the complexity of the one-sided UNDE systems, such as reverberation, and acoustic shadowing.

Acknowledgment

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