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Extended Target Localization with Total-Variation Denoising in Through-the-Wall-Imaging

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***Abstract*—We propose a target detection and clutter removal technique for through the wall radar imaging that captures the extended reflections of targets behind the wall and determines target consistency using total variation denoising. Our approach is based on the multipath elimination by sparse inversion (MESI) algorithm which models the clutter removal problem as a structured blind deconvolution problem with sparsity constraints on the scene and the multipath reflections. In this work, we extend the MESI algorithm by incorporating the spatial correlation of extended target reflections into the target detection stage. This in turn improves the clutter mitigation performance by ensuring that a separate convolution kernel is computed for each detected target to match the corresponding multipath reflections. When MIMO measurements are available, we apply total variation denoising on the clutter-suppressed SIMO images followed by incoherent summation to generate a single noise free target image. We present numerical experiments that demonstrate the improved performance of our approach compared to standard MESI and MIMO imaging.**

***Keywords*—Through-the-wall-imaging, multi-path elimination, sparse recovery, compressed sensing, total-variation denoising**

I. Introduction

Through-the-wall-imaging (TWI) has been developed for localizing and detecting objects inside enclosed structures with applications in surveillance for urban environments and rescue missions for natural disasters [1]. The technology relies on transmitting an electromagnetic radar pulse which propagates through the outside wall of the structure, reflects off the internal targets then propagates back to a receiver antenna array [2]. However, the received signal is often corrupted by indirect secondary reflections from the internal walls which result in ghost artifacts in the reconstructed image.

Several works in the literature have addressed the ghost artifacts arising from multipath reflections. In [3]–[6], the scene geometry is assumed to be known and the multipath model is incorporated into the image reconstruction algorithms, thereby improving the imaging performance by reducing false positives. The current trend in literature is to make no assumptions about the underlying scene geometry. Clutter removal in TWI is then formulated as a blind sparse-deconvolution problem. In this context, Mansour and Liu [7] proposed a multipath-elimination by sparse inversion (MESI) algorithm that removes the clutter by iteratively recovering the primary impulse responses of targets followed by estimation of corresponding convolution operators that result in multi-path reflections in the received data. More recently, Leigsnering *et al.* [8] combined target sparsity with multi-path modeling to achieve further improvements in the quality of TWI with uncertainties in wall-parameters that are solved via alternating optimization.

The above works assume a sparse model for the scene where the desired reflections are induced by individual point targets. However, in practical scenes, targets produce an extended radar reflection which is not fully captured by the sparse representations. In [9]–[11], synchronized multiple antenna arrays are combined to capture the extended reflections of targets. In this paper, we propose a modification of the MESI algorithm that allows us to capture the extended reflections of targets behind the wall and suppress clutter using a single antenna array. We start by defining the image reconstruction task in Section II as a sparse blind deconvolution problem and give an overview of the MESI framework of [7]. We then proceed to describe our extended target detection technique in Section III which improves the ability of MESI to compute the clutter generating convolution operator. We also employ total variation denoising applied to multiple clutter-suppressed SIMO images to enhance the target image compared to MIMO imaging. Finally, we demonstrate the performance of our proposed technique in Section IV in localizing extended target reflections in a finite-difference time-domain (FDTD) simulated TWI scene with multiple targets.

II. Background

A. Signal model

Consider a monostatic physical aperture radar with a one dimensional array of antennas having a single transmitting source and n_r receivers. Let s be the time-domain waveform of the pulse that is transmitted by the source.

Without loss of generality, suppose that there are K targets in the scene. The time domain primary impulse response of a target indexed by $k \in \{1 \dots K\}$ at receiver $n \in \{1 \dots n_r\}$ is denoted by $g_k(n)$. This results in a clutter free received signal $r(n) = s * g_k(n)$, where $r(n) \in \mathbb{R}^{n_t}$ is the n_t dimensional time-domain measurement, and $*$ is the convolution operator. Moreover, suppose that the scene is divided into an $N_x \times N_y$ spatial grid and let $x_k \in \mathbb{C}^{N_x N_y}$ be the target response in the image domain, such that, x_k is zero everywhere except on the support of the target position. For a point target, we can express the impulse response

$$g_k(n) = \int_{\omega \in \mathbb{R}} e^{i\omega t} e^{-i\omega \tau_k(n)} x_k \mathrm{d}\omega, \quad (1)$$

where $\tau_k(n)$ is the roundtrip time from the source to the target k and back to receiver n. Suppose that we discretize the frequency bandwidth into n_f bins, and let $W_n \in \mathbb{C}^{n_f \times N_x N_y}$ be the delay and sum operator of receiver n, such that $W_n(\omega, j) = e^{-i\omega\tau_j(n)/c}$, where $\tau_j(n)$ is the roundtrip time from the source to a grid point $j \in N_x \times N_y$ and back to the receiver n.

We assume in this work that for every target k, all receivers view a multipath / clutter response $m_k(n)$ as the convolution of the corresponding primary response $g_k(n)$ with the same clutter inducing delay kernel d_k, i.e. $m_k(n) = g_k(n) * d_k$. Consequently, the received signal at receiver n is modeled as

$$\begin{aligned} r(n) &= s * \sum_{k=1}^{K} (g_k(n) + m_k(n)) \\ &= s * \sum_{k=1}^{K} (g_k(n) + d_k * g_k(n)), \end{aligned} \tag{2}$$

where d_k is independent of the receiver location n.

In this context, our goal is to estimate the delay kernels d_k and the target responses x_k for all targets in the scene given only the received signals $r(n)$ for all $n \in \{1, \ldots n_r\}$. We build our solution as an enhancement to the MESI [7] framework reviewed below.

B. Multipath Elimination by Sparse Inversion (MESI)

The MESI algorithm identifies the primary targets and removes wall clutter by alternating between two steps: (1) estimation of a sparse target response; (2) estimation of a delay convolution operator that matches the primary response to possible clutter in the received signals. In what follows, we denote by the superscripted $\hat{v}$ the frequency response of a vector v.

Given a set of measurements, let the vector $\mathbf{r} \in \mathbb{R}^{n_t n_r}$ be composed by stacking the received signals $r(n)$ for all receivers $n \in \{1, \ldots n_r\}$, and let $\mathbf{W}$ be the SIMO imaging matrix composed by stacking the delay-and-sum operations W_n. Define the forward model f as follows

$$f(g_k, d_k, s) := s * (g_k + d_k * g_k), \tag{3}$$

and let $\mathbf{r}_x = \mathbf{r} - \sum_{j=1}^{k-1} f(g_j, d_j, s)$ be the residual measurement at iteration k, where the g_j is computed from x_j using (1).

Then MESI algorithm proceeds by alternating between the following two minimization stages. In the first stage, an estimate of the target response $\tilde{x}_k$ is computed by solving

$$\tilde{x}_k = \arg\min_x \|\hat{\mathbf{r}}_x - \hat{s} \odot (\mathbf{W}x)\|_2 \text{ subject to } \|x\|_1 \leq \sigma_x, \tag{4}$$

where $\odot$ is an element-wise Hadamard product, and σ_x is an appropriate sparsity bound. In the second stage, the residual measurements are updated to $\mathbf{r}_d = \mathbf{r}_x - s * g_k$, and the corresponding delay convolution operator is given by

$$\tilde{d}_k = \arg\min_d \|\mathbf{r}_d - s * (d * g_k)\|_2 \text{ subject to } \|d\|_1 \leq \sigma_d, \tag{5}$$

where again σ_d is an appropriate sparsity bound on d. Above two steps are repeated until a preset maximum iteration number is reached or a data mismatch is reached. The target image $\tilde{\mathbf{x}}$ is finally computed by summing the $\tilde{x}_k$ over all iterations k.

III. Proposed Approach

In this section, we report two extensions to MESI that significantly improve its performance.

A. Extended target detection

One limitation of the traditional MESI approach is that at a given iteration k it may fail to capture the entire target response x_k. Consequently, the delay convolution operator computed at that iteration does not necessarily correspond to the actual target, which typically leads to a degradation in performance. Accordingly, the performance of imaging can be significantly improved by recognizing and extracting all the pixels corresponding to the same target. This can be practically achieved by replacing (4) with a detector for the strongest reflector as follows

$$\bar{x}_k = \arg\min_x \|\hat{\mathbf{r}}_x - \hat{s} \odot (\mathbf{W}x)\|_2 \text{ subject to } \|x\|_0 = 1. \tag{6}$$

The extended target reflection $\tilde{x}_k$ is then computed by scanning the spatial neighborhood around $\bar{x}_k$ and assigning all the connected pixels to the same target k. Our implementation thus compares the relative energy difference between the strongest reflector and a pixel in the neighborhood as illustrated in Fig. 1. If the relative energy is higher than a given threshold relative to the peak, we accept that pixel as a part of the extended target, otherwise we discard it as the background.

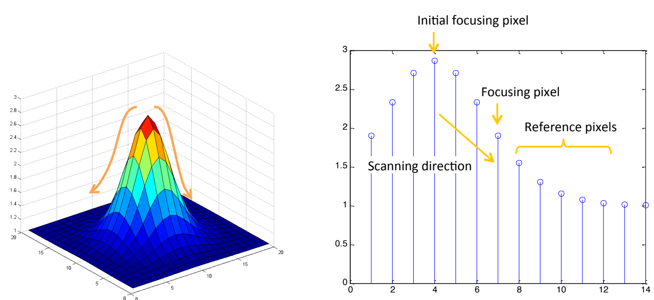


Fig. 1: Illustration of the extended target detection procedure.

B. Noise mitigation with total variation

Consider a MIMO setup as in Fig. 2 where the position of the transmitter is continuously changed to obtain several views of the region of interest. Specifically, we perform n_s distinct measurements each corresponding to a particular transmitter location.

Observation of a scene under different arrangement of transmitter and receiver pairs can allow us to mitigate the clutter due to multi-path and reduce the amount of noise in the reconstructed image. The underlying assumption is that by changing the positions of the transmitter and receiver iteratively, the profile of target reflections will have a consistent response, whereas the reflections from indirect path will have a random noise-like behavior. Accordingly, we propose to use total variation (TV) denoising [12] in order to separate pixels corresponding to actual targets from those corresponding to

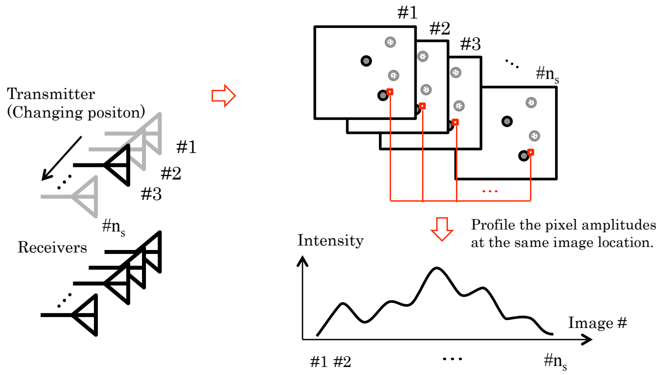
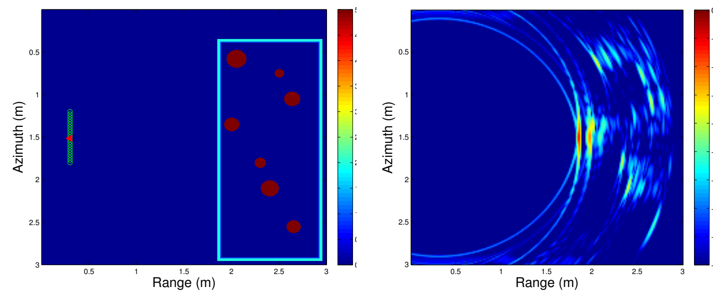
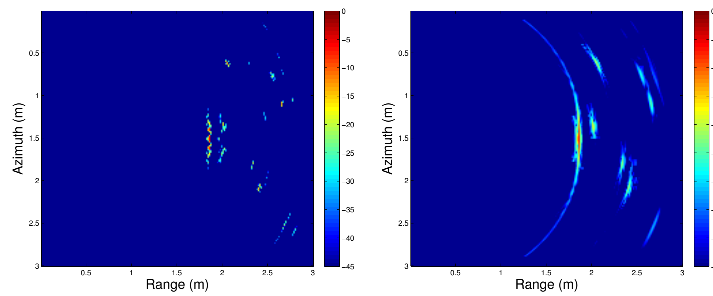


Fig. 2: MIMO antenna setup and profile of pixel amplitudes at a specific image location for multiple SIMO images.



(a) (b)

Fig. 3: (a) Schematic of the simulation layout where the color bar indicates the relative permittivity. (b) Imaging results in dB of the simulated scene using standard delay and sum backprojection.



(a) (b)

Fig. 4: Imaging results using (a) sparse MESI of [7], and (b) enhanced MESI with extended target detection.

various types of noise. Given a stack of noisy images $\tilde{\mathbf{x}}$, we formulate denoising as following optimization problem

$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left\{ \frac{1}{2} \|\mathbf{x} - \tilde{\mathbf{x}}\|_2^2 + \lambda \mathrm{TV}(\mathbf{x}) \right\}, \tag{7}$$

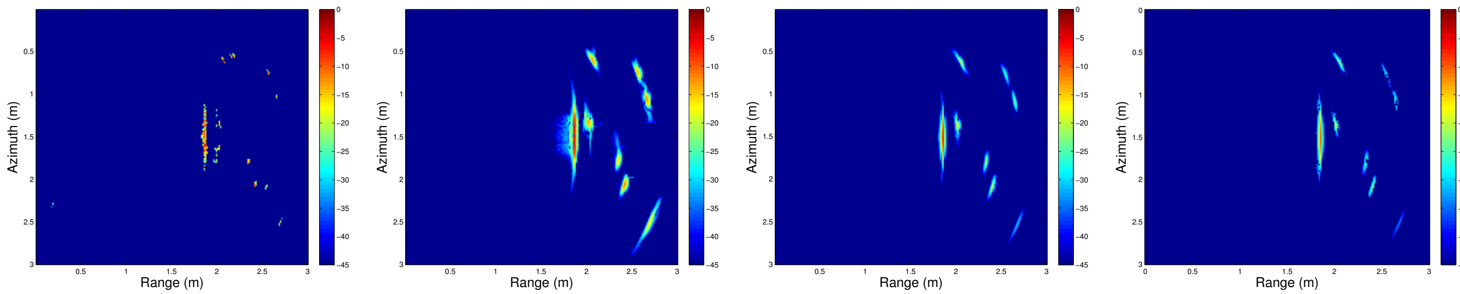
where $\lambda > 0$ is the regularization parameter that controls the amount of denoising to apply. TV is a popular method in image processing for estimating signals that have piecewise-smooth profiles, which suits our objective of determining the profiles of targets. Our implementation is based on fast iterative shrinkage/thresholding algorithm (FISTA) [13] that acts on a stack of images, where each image corresponds to a particular transmitter location. We observed that the combination of extended target detection with TV denoising yields excellent results as corroborated by our numerical experiments.

IV. Numerical Experiments

To examine the performance of our algorithm, we consider 7 metal cylinders situated in a rectangular shaped room of size 2.6m wide and 1.2m long, with top schematic view shown in Fig. 3a. The four-side wall is composed of two layers, with thickness 3cm and 1.2cm, and relative permittivity $\epsilon_r = 10$ and $\epsilon_r = 5$ for the outer layer and the inner layer respectively. A 21-element sensor array (n_r=21) is placed 1.2m far to the left of the room, with the inter-element spacing 3cm corresponding to the half wavelength of pulse central frequency. The elements of the array are line sources/receivers with the electric fields vertically polarized parallel to the cylinder axes. We use a 2D finite-difference time-domain (FDTD) simulator to transmit a derivative Gaussian pulse and record radar echoes by all elements. Imaging process is then implemented on the received radar echoes. When we perform imaging using the conventional delay-and-sum method for a SIMO scenario where the center (11th) element acts as the transmitter, we observe ghost images of the cylinders due to multi-path propagation within the wall as shown in Fig. 3b. Using the MESI algorithm of [7] succeeds in significantly reducing the clutter, however, some multipath reflections remain visible in the reconstructed image as can be seen in Fig. 4a. On the other hand, Fig. 4b shows that the MESI algorithm with extended target detection successfully finds the primary reflection and completely eliminates the corresponding multi-path reflections.

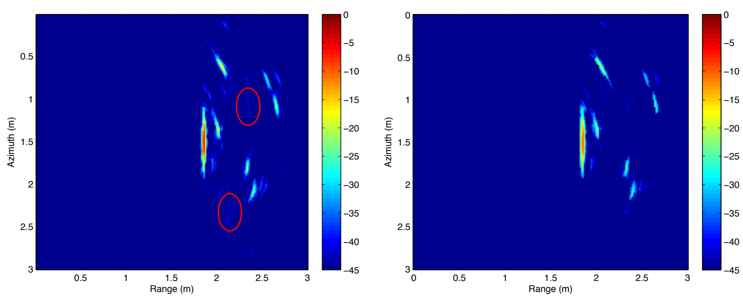
To improve the imaging result, we consider a MIMO acquisition scenario where the 21 receiving antennas also act as $n_s = 21$ transmitting antennas. We compare the recovery performance using MESI with extended target detection and incoherently summing of n_s SIMO images after TV denoising in Fig. 5. Examining the n_s SIMO images, we observe that the pixels of extended targets exhibit continuous strong intensities across the n_s images, while the pixels of clutter exhibit some extent discontinuity. With the aforementioned TV-based denoising process, we can improve the imaging result by eliminating potential clutter pixels while keeping only target pixels. The results show that incoherently summing the n_s images with clutter pixels removed achieves a sharper target image compared to the other schemes.

Next we tested the imaging performance from noisy measurements obtained by adding Gaussian random noise to the measurements to achieve a signal to noise ratio (SNR) of 10dB. We compare the recovery performance of our scheme with TV denoising to enhancend MESI without TV denoising. The results are presented in Fig. 6. It can be seen that reconstruction with TV denoising is better capable at removing the noise from the image as highlighted by the circled regions in Fig. 6b.



(a) (b) (c) (d)

Fig. 5: Imaging results using (a) sparse MESI of [7] with MIMO imaging operator, and (b–d) enhanced MESI using extended target detection with (b) MIMO imaging operator, (c) SIMO imaging operator with incoherent addition, and (d) SIMO imaging and TV regularization with incoherent addition.



(a) (b)

Fig. 6: Imaging results from noisy measurements at 10dB SNR using (a) enhanced MESI with incoherent SIMO imaging, and (b) enhanced MESI with incoherent SIMO imaging and TV denoising.

V. Conclusion

In conclusion, we presented a method that enhances the performance of the MESI algorithm of [7] by detecting extended object reflections instead of non-structured sparse scene reflectors. Our method also limits the estimation of a delay convolution kernel to each potential target thereby improving the clutter removal performance. We demonstrated through numerical simulations the improved behavior for both SIMO and MIMO measurements. When MIMO measurements are available, we also proposed a robust imaging scheme that first computes a set of SIMO images using our extended target MESI approach followed by total variation denoising and incoherent summation of the denoised SIMO images. Our simulations demonstrated that the proposed scheme results in a better image quality compared to imaging with a MIMO imaging operator.

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References

[1] M. G. Amin and F. Ahmad, "Through-the-wall radar imaging: Theory and applications," *Radar Signal Processing Section, E-Reference Signal Processing, Elsevier*, 2013.

[2] T. S. Ralston, G. L. Charvat, and J. E. Peabody, "Real-time through-wall imaging using an ultrawideband multiple-input multiple-output (MIMO) phased array radar system," in *IEEE International Symposium on Phased Array Systems and Technology (ARRAY)*, 2010, pp. 551–558.

[3] P. Setlur, M. Amin, and F. Ahmad, "Multipath model and exploitation in through-the-wall and urban radar sensing," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 10, pp. 4021–4034, 2011.

[4] P. Setlur, G. Alli, and L. Nuzzo, "Multipath exploitation in through-wall radar imaging via point spread functions," *IEEE Transactions on Image Processing*, vol. 22, 2013.

[5] M. Leigsnering, F. Ahmad, M. G. Amin, and A. M. Zoubir, "Compressive Sensing Based Specular Multi-path Exploitation for Through-the-wall Radar Imaging," in *Proc. of the IEEE ICASSP*, March 2013.

[6] M. Leigsnering, F. Ahmad, M. Amin, and A. Zoubir, "Multipath exploitation in through-the-wall radar imaging using sparse reconstruction," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 50, no. 2, pp. 920–939, April 2014.

[7] H. Mansour and D. Liu, "Blind multi-path elimination by sparse inversion in through-the-wall-imaging," in *Proc. IEEE 5th Int. Workshop on Computational Advances in Multi-Sensor Adaptive Process. (CAMSAP)*, St. Martin, December 15-18, 2013, pp. 256–259.

[8] M. Leigsnering, F. Ahmad, M. G. Amin, and A. M. Zoubir, "CS based specular multipath exploitation in TWRI under wall position uncertainties," in *Proc. 8th IEEE Sensor Array and Multichannel Signal Processing Workshop*, Coruña, Spain, June 22-25, 2014, pp. 481–484.

[9] M. Dehmollaian and K. Sarabandi, "Refocusing through building walls using synthetic aperture radar," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no. 6, pp. 1589–1599, 2008.

[10] C. Debes, "Advances in detection and classification for through the wall radar imaging," Ph.D. dissertation, Technische Universitt Darmstadt, 2010.

[11] A. N. Gaikwad, D. Singh, and M. J. Nigam, "Recognition of target in through wall imaging using shape feature extraction," in *Proc. of the IEEE International Geosciences and Remote Sensing Symposium*, 2011, pp. 957–960.

[12] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D*, vol. 60, no. 1–4, pp. 259–268, November 1992.

[13] A. Beck and M. Teboulle, "Fast gradient-based algorithm for constrained total variation image denoising and deblurring problems," *IEEE Trans. Image Process.*, vol. 18, no. 11, pp. 2419–2434, November 2009.