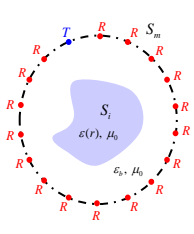


## Abstract

Newton-type algorithms have been extensively studied in nonlinear microwave imaging due to their quadratic convergence rate and ability to recover images with high contrast values. In the past, Newton methods have been implemented in conjunction with smoothness promoting optimization/regularization schemes. However, this type of regularization schemes are known to perform poorly when applied in imaging domains with sparse content or sharp variations. In this work, an inexact Newton algorithm is formulated and implemented in conjunction with a linear sparse optimization scheme. A novel preconditioning technique is proposed to increase the convergence rate of the optimization problem. Numerical results demonstrate that the proposed framework produces sharper and more accurate images when applied in sparse/sparsified domains.

## Formulation

### 2D Electromagnetic Equations:



$R$  = Receiver,  
 $T$  = Transmitter,  
 $\epsilon(r)$  = permittivity  
 $S_i$  = investigation domains  
 $S_m$  = measurement domains  
 $r$  = 2D position vector

### TMz sources:

$$E_z^{\text{inc}}(r) = -j\omega\mu_0 I_e G_{2D}(r, r_T)$$

### Contrast-Source Equations (EFIE):

For a given  $i^{\text{th}}$  excitation:

$$J_i(r) - \chi(r)E_i^{\text{inc}}(r) - k_b^2 \chi(r) \int_{S^{\text{inv}}} J_i(r')G(r, r')dr' = T_i^1(\chi, J_i) = 0, \quad r \in S^{\text{inv}}$$

$$E_i^{\text{scat}}(r) = k_b^2 \int_{S^{\text{inv}}} J_i(r')G(r, r')dr' = T_i^2(J_i), \quad r \in S^{\text{inv}}$$

### Definition of the nonlinear operator:

$$T(z) = \begin{pmatrix} T_1^1(\chi, J_1) \\ T_2^1(\chi, J_2) \\ \vdots \\ T_{N^T}^1(\chi, J_{N^T}) \\ T_1^2(J_1) \\ T_2^2(J_2) \\ \vdots \\ T_{N^T}^2(J_{N^T}) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ E_1^{\text{scat}}(r) \\ E_2^{\text{scat}}(r) \\ \vdots \\ E_{N^T}^{\text{scat}}(r) \end{pmatrix} = y, \quad f(z) = T(z) - y = 0$$

### Inexact Newton:

$$\partial_z f(z_k)(h_k) = -f(z_k) \quad \text{solve for } h_k$$

$$z_{k+1} = z_k + h_k$$

### Frchet derivative matrix:

$$\partial_z T(z) = \begin{pmatrix} \partial_\chi T_1^1|_z & \partial_{J_1} T_1^1|_z & 0 & 0 & \dots & 0 \\ \partial_\chi T_2^1|_z & 0 & \partial_{J_2} T_2^1|_z & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \partial_\chi T_{N^T}^1|_z & 0 & 0 & 0 & \dots & \partial_{J_{N^T}} T_{N^T}^1|_z \\ 0 & \partial_{J_1} T_1^2|_z & 0 & 0 & \dots & 0 \\ 0 & 0 & \partial_{J_2} T_2^2|_z & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \partial_{J_{N^T}} T_{N^T}^2|_z \end{pmatrix}$$

where:

$$\partial_\chi T_i^1|_z(h_\chi) = -h_\chi(r)[E_i^{\text{inc}}(r) + k_b^2 \int_{S^{\text{inv}}} J_i(r')G(r, r')dr'], \quad r \in S^{\text{inv}}$$

$$\partial_{J_i} T_i^1|_z(h_{J_i}) = h_{J_i}(r) - k_b^2 \chi(r) \int_{S^{\text{inv}}} h_{J_i}(r')G(r, r')dr', \quad r \in S^{\text{inv}}$$

$$\partial_{J_i} T_i^2|_z(h_{J_i}) = k_b^2 \int_{S^{\text{inv}}} h_{J_i}(r')G(r, r')dr', \quad r \in S^{\text{inv}}$$

### Discretization:

Under  $N^{\text{th}}$  cell discretization the variables become:

$$\bar{\chi} = [\chi_1, \chi_2, \dots, \chi_N]^T$$

$$\bar{J}_i = [J_{i,1}, J_{i,2}, \dots, J_{i,N}]^T$$

$$\bar{E}_i^{\text{inc}} = [E_{i,1}^{\text{inc}}, E_{i,2}^{\text{inc}}, \dots, E_{i,N}^{\text{inc}}]^T$$

$$\bar{h}_\chi = [h_{\chi_1}, h_{\chi_2}, \dots, h_{\chi_N}]^T$$

$$\bar{h}_{J_i} = [h_{J_{i,1}}, h_{J_{i,2}}, \dots, h_{J_{i,N}}]^T$$

The Frchet derivatives become:

$$\partial_\chi \bar{T}_i^1|_z(\bar{h}_\chi) = D\{-\bar{E}_i^{\text{inc}} - \bar{G}^{\text{inv}} \bar{J}_i\} \bar{h}_\chi$$

$$\partial_{J_i} \bar{T}_i^1|_z(\bar{h}_{J_i}) = [\bar{I} - D\{\bar{\chi}\} \bar{G}^{\text{inv}}] \bar{h}_{J_i}$$

$$\partial_{J_i} \bar{T}_i^2|_z(\bar{h}_{J_i}) = \bar{G}^{\text{m}} \bar{h}_{J_i}$$

where  $D\{\cdot\}$  is a function that transforms the input vector into a diagonal matrix. The block matrices are the integration of the green function computed as:

$$\{\bar{G}^{\text{m,inv}}\}_{mn} = k_b^2 \int_{S^{\text{inv}} \in S_n} G(r_m, r') dr', \quad r_m \in S^{\text{inv}}$$

$$\{\bar{G}^{\text{m,inv}}\}_{mn} = k_b^2 \int_{S^{\text{inv}} \in S_n} G(r_m, r') dr', \quad r_m \in S^{\text{inv}}$$

### Preconditioning:

to tackle the variables unit mismatch in the solution, preconditioning is required:

$$\bar{L}_k = \left( \sqrt{D\{T[\partial_z \bar{T}^n(\bar{z}_k) \partial_z \bar{T}^n(\bar{z}_k)]\}} \right)^{-1}$$

$$\bar{R}_k = \left( \sqrt{D\{T[\partial_z \bar{T}^n(\bar{z}_k) \partial_z \bar{T}^n(\bar{z}_k)]\}} \right)^{-1}$$

### Sparse Preconditioned Inexact Newton:

In the following, a pseudo-code for the complete modified-preconditioned inexact algorithm with sparse optimization is written:

```
initialize  $\delta, \gamma, \bar{z}_0 = 0$ 
for  $k = 1, \dots, N_{\text{it}}^{\text{Newton}}$ 
  compute  $\partial_z \bar{F}(\bar{z}_k) = \partial_z \bar{T}(\bar{z}_k)$ 
  compute  $\bar{F}(\bar{z}_k) = \bar{T}(\bar{z}_k) - \bar{y}$ 
  normalization  $\bar{F}^{\text{np}}(\bar{z}_k) = \bar{F}(\bar{z}_k) / \sigma_1^2$ 
   $\partial_z \bar{F}^{\text{np}}(\bar{z}_k) = \partial_z \bar{F}(\bar{z}_k) / \sigma_1^2$ 
  Preconditioning  $\bar{F}^{\text{pp}}(\bar{z}_k) = \bar{L}_k \bar{F}^{\text{np}}(\bar{z}_k)$ 
   $\partial_z \bar{F}^{\text{pp}}(\bar{z}_k) = \bar{L}_k \partial_z \bar{F}^{\text{np}}(\bar{z}_k) \bar{R}_k$ 
   $\bar{h}_k = \arg \min_{\bar{h}} \frac{1}{2} \|\bar{F}^{\text{pp}}(\bar{z}_k) - \partial_z \bar{F}^{\text{pp}}(\bar{z}_k) \bar{h}\|_2^2 + \gamma_k \|\bar{h}\|_{0,1}$ 
   $\bar{z}_{k+1} = \text{Thrs}^{\text{sh}}(\bar{z}_k + \bar{h}_k)$ 
   $\gamma_{k+1} = \delta \gamma_k$ 
  If  $\|\bar{z}_{k+1} - \bar{z}_k\|_2 / \|\bar{z}_{k+1}\|_2 < \epsilon^{\text{Newton}}$ , break
end
```

### Two-Step Iterative Shrinkage Thresholding (TWIST):

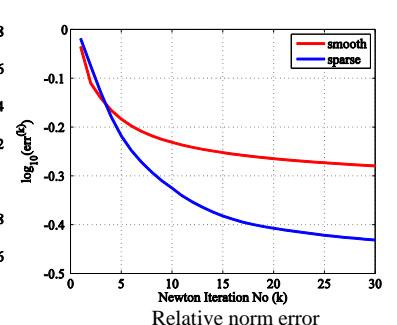
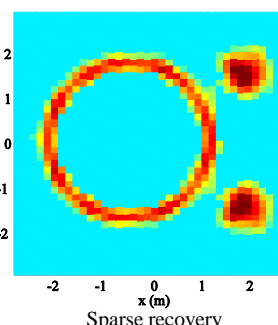
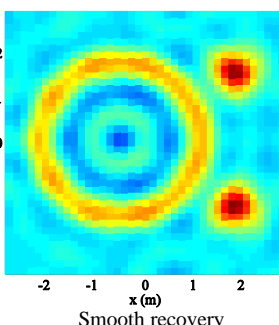
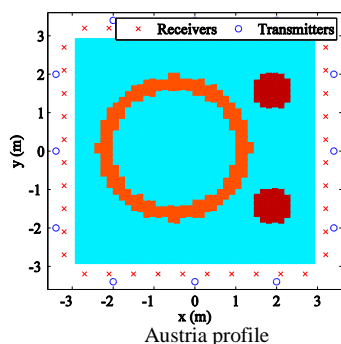
In the following, a pseudo-code for the TWIST algorithm to solve the sparse linear optimization problem.

```
Initialize  $\sigma_m, \gamma$ 
set  $\rho = (1 - \sqrt{\xi_1 / \xi_m}) / (1 + \sqrt{\xi_1 / \xi_m})$ 
 $\alpha = \rho^2 + 1$ 
 $\zeta = 2\alpha / (\xi_1 + \xi_m)$ 
 $\bar{h}^{(k)} = T^{\gamma_k}(\bar{h}^{(k-1)} - \partial_z \bar{F}^{\text{pp}*}(\bar{z}_k)[\bar{F}^{\text{pp}}(\bar{z}_k) + \partial_z \bar{F}^{\text{pp}}(\bar{z}_k) \bar{h}^{(k-1)}])$ 
For  $i = 1, \dots, N_{\text{it}}^{\text{TWIST}}$ 
   $\bar{h}_{(i+1)}^{(k)} = (\alpha - \zeta) \bar{h}_{(i)}^{(k)} + (1 - \alpha) \bar{h}_{(i-1)}^{(k)}$ 
   $+ \zeta \text{Thrs}^{\gamma_k}(\bar{h}_{(i)}^{(k)} - \partial_z \bar{F}^{\text{pp}*}(\bar{z}_k)[\bar{F}^{\text{pp}}(\bar{z}_k) + \partial_z \bar{F}^{\text{pp}}(\bar{z}_k) \bar{h}_{(i)}^{(k)}])$ 
  If  $\|\bar{h}_{(i+1)}^{(k)} - \bar{h}_{(i)}^{(k)}\|_2 / \|\bar{h}_{(i+1)}^{(k)}\|_2 < \epsilon^{\text{Sparse}}$ , break
end
set  $\bar{h}_k = \bar{h}_{(i+1)}^{(k)}$ 
```

## Numerical Results

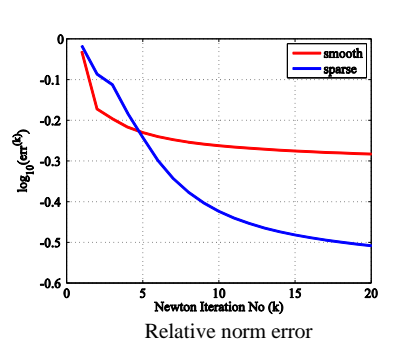
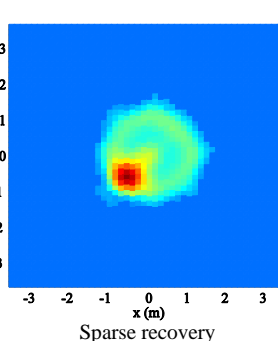
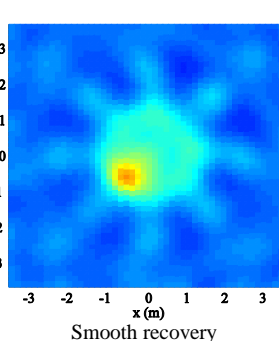
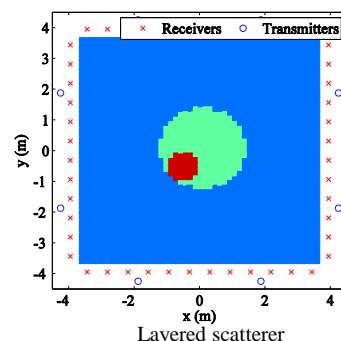
### Austria example:

40 receivers, 12 transmitters, Sparseness level: 15%,  $N = 1600$ , Dimensions:  $6\text{m} \times 6\text{m}$ ,  $f = 150\text{MHz}$ . For smooth reconstruction, truncated Lnadweber is used, truncated at 50 iterations. TWIST iterations has been also truncated at 50 iterations within each Newton iterations. TWIST parameters are  $\delta = 0.7$ ,  $\gamma = 2.5$ ,  $\sigma_m = 0.45$ .



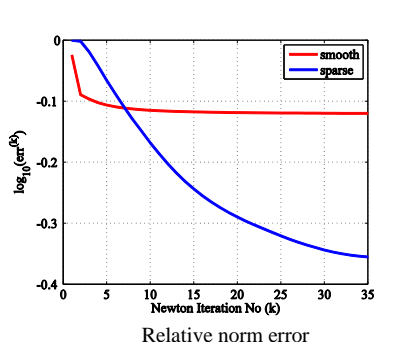
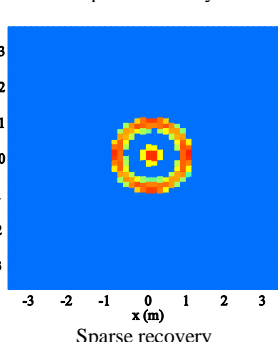
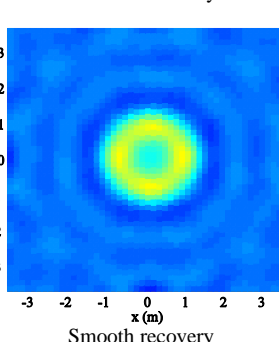
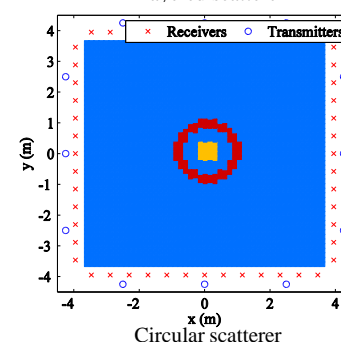
### Layered example:

48 receivers, 8 transmitters, Sparseness level: 9.9%,  $N = 2500$ , Dimensions:  $7.5\text{m} \times 7.5\text{m}$ ,  $f = 125\text{MHz}$ . For smooth reconstruction, truncated Lnadweber is used, truncated at 50 iterations. TWIST iterations has been also truncated at 50 iterations within each Newton iterations. TWIST parameters are  $\delta = 0.6$ ,  $\gamma = 2$ ,  $\sigma_m = 0.45$ .



### Circular example:

52 receivers, 12 transmitters, Sparseness level: 3.36%,  $N = 2500$ , Dimensions:  $7.5\text{m} \times 7.5\text{m}$ ,  $f = 125\text{MHz}$ . For smooth reconstruction, truncated Lnadweber is used, truncated at 50 iterations. TWIST iterations has been also truncated at 50 iterations within each Newton iterations. TWIST parameters are  $\delta = 0.85$ ,  $\gamma = 3$ ,  $\sigma_m = 0.45$ .



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