# MT3D_INV: <br> A 3D MT Inversion Algorithm 

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Gregory A. Newman \& Michael Commer
Earth Sciences Division
Lawrence Berkeley National Laboratory Berkeley California

## Inverse Problem Formulation

Minimize the cost functional:

$$
\varphi=\sum_{j=1}^{2 N}\left\{\left(Z_{j}^{o b s}-Z_{j}^{p}\right) D_{j}\right\}^{2}+\lambda m \mathbf{W}^{T} \mathbf{W} \mathbf{m} .
$$

$Z^{\text {obs }}$ and $\mathbb{Z}^{\mathrm{p}}$ are N observed and predicted impedances
$\mathrm{D}=$ data weights
$\mathrm{m}=\mathrm{M}$ conductivity model parameters.
$\mathbf{W}=\nabla^{2}$ operator; constructs a smooth model
$\lambda=$ tradeoff parameter

## Non-Linear Conjugate Gradients

We need the gradient of the cost functional

$$
\nabla_{\mathrm{m}} \varphi=\nabla \varphi_{\mathrm{d}}+\nabla \varphi_{\mathrm{m}}
$$

Ability to determine a scalar $\alpha$ such that

$$
\varphi(\mathbf{m}+\alpha \mathbf{p})
$$

is minimized along the conjugate search direction $\mathbf{p}$

## Computational Efficiencies

Gradient requires 4 applications of the forward code at each frequency
Line search usually requires 2 forward modeling applications at each frequency
Typically four forward modeling applications per frequency needed per inversion iteration
Ideal method for problems with extremely large data sets and model parameterizations Algorithm implemented on the Franklin-Cray XT4 machine at NERSC: 9660 nodes/19320 cores

## An Iterative Solution

Make initial model guess

Select tradeoff parameter $\lambda$

During the iteration process $\lambda$ is reduced (this can help accelerate convergence)

## Dublin Model Example

Inversion launched with $100 \Omega$. m halfspace
9912 data points $\left(Z_{x x}, Z_{x y}, Z_{y x}, Z_{y y}\right)$ used all 21 frequencies; 59 detector locations
Data weighting:
$Z_{x x}$ weights $\Rightarrow 5 \%\left\|Z_{x y}\right\| \quad Z_{x y}$ weights $\Rightarrow 5 \%\left\|Z_{x y}\right\|$
$Z_{y x}$ weights $=>5 \%\left\|Z_{y x}\right\| \quad Z_{y y}$ weights $=>5 \%\left\|Z_{y y}\right\|$
$\sim 10^{7}$ resistivity parameters imaged Problem solved on 64 cores

## Dublin Test Model

looking from
positive to negative $x$ negative to positive $x$
 ---gative

## Coordinate Systems



Coordinate systems related to each other by a -90 degree rotation

$$
\left(\begin{array}{cc}
Z_{y y}-Z_{y x} \\
-Z_{x y} & Z_{x x}
\end{array}\right)_{\text {yours }}=\left(\begin{array}{cc}
\cos \phi & -\sin \phi \\
\sin \phi & \cos \phi
\end{array}\right)\left(\begin{array}{cc}
Z_{x x} & Z_{x y} \\
Z_{y x} & Z_{y y}
\end{array}\right)_{\text {mine }}\left(\begin{array}{ll}
\cos \phi & \sin \phi \\
-\sin \phi & \cos \phi
\end{array}\right)_{\varphi=-\frac{\pi}{2}}
$$

z positive downward for both

## Inversion Metrics





## $Z_{\mathrm{xy}}$ Apparent Resistivity Fits





## $\mathrm{Z}_{\mathrm{yx}}$ Impedance Phase Fits



## $Z_{\mathrm{xy}}$ Impedance Phase Fits





## $Z_{x y}$ Impedance Phase Fits





Resistivity Image in Cross Section


## Outstanding Issues

## Static Shifts

## Survey Aperture \& Station Density

Meshing

Model Stabilization

Resistivity Image in Cross Section


## Resistivity Image in Depth Section





## $Z_{x y}$ Apparent Resistivity Fits





## $\mathrm{Z}_{\mathrm{yx}}$ Impedance Phase Fits



## $Z_{x y}$ Impedance Phase Fits





## Survey Layout in my coordinate system




## The Forward Problem

## The electric field vector equation for MT:

## $\nabla \times \nabla \times \mathbf{e}+i \omega \mu \sigma \mathrm{e}=\mathbf{0}$.

equation approximated on staggered FD grid

## The Krylov Solver

assemble complex-symmetric sparse linear system

$$
\mathrm{Ke}=\mathrm{s}
$$

s depends on MT source polarization
(two for each frequency)
solve system with iterative Krylov methods
(also employ static divergence correction to improve convergence)
magnetic field then determined from Faraday's law

## Computation of the Gradients

Evaluation of $\nabla \varphi_{\mathrm{m}}$ leads to

$$
\nabla \varphi_{\mathrm{m}}=2 \mathbf{W}^{\mathrm{t}} \mathbf{W} \mathbf{m} .
$$

## Computation of the Gradients

As for $\nabla \varphi_{d}$, let $\Delta Z_{j}=\left\{\left(Z_{j}^{\text {obs }}-Z_{j}^{p}\right) / \varepsilon_{j}^{2}\right\}$ be complex,

$$
\partial \varphi_{d} / \partial m_{k}=-2 \operatorname{Re} \sum_{j=1}^{N}\left(\Delta Z_{j}\right)^{*} \partial Z_{j} / \partial m_{k},
$$

or N
$\partial \varphi_{\mathrm{d}} / \partial \mathrm{m}_{\mathrm{k}}=2 \operatorname{Re} \Sigma\left(\Delta Z_{\mathrm{j}}\right)^{* 1} \mathbf{g}_{\mathrm{j}}^{\mathrm{t}} \mathbf{K}^{-1}\left(\partial \mathbf{K} / \partial \mathrm{m}_{\mathrm{k}} \mathbf{E}_{1}\right)+$

$$
j=1
$$

$$
2 \operatorname{Re} \sum_{j=1}^{N}\left(\Delta Z_{j}\right)^{*}{ }^{2} \mathbf{g}_{j}{ }^{t} \mathbf{K}^{-1}\left(\partial \mathbf{K} / \partial m_{k} \mathbf{E}_{2}\right) .
$$

* stands for complex conjugation.


## The Non Linear CG Algorithm

(1) Choose $\mathbf{m}_{(1)}$ and select $\mathbf{p}_{(1)}=-\mathbf{M}_{(1)}^{-1} \nabla_{\varphi}\left(\mathbf{m}_{(1)}\right)$
(2) find $\alpha(\mathrm{i})$ that minimizes $\varphi\left(\mathrm{m}_{(\mathrm{i})}+\alpha(\mathrm{i}) \mathbf{p}_{(\mathrm{i})}\right)$
(3) set $\mathbf{m}_{(\mathrm{i}+1)}=\mathbf{m}_{(\mathrm{i})}+\alpha(\mathrm{i}) \mathbf{p}_{(\mathrm{i})}$ and $\mathbf{r}_{(\mathrm{i}+1)}=-\nabla \varphi\left(\mathbf{m}_{(\mathrm{i}+1)}\right)$
(4) $\beta(\mathrm{i}+1)=\left\{\left(\mathbf{r}_{(\mathrm{i}+1)}{ }^{\mathrm{t}} \mathrm{M}_{(\mathrm{i}+1)}^{-1} \mathbf{r}_{(\mathrm{i}+1)}-\mathbf{r}_{(\mathrm{i}+1)} \mathrm{M}_{(\mathrm{i}+1)}^{-1 \mathrm{t}} \mathbf{r}_{(\mathrm{i})}\right) / \mathbf{r}_{(\mathrm{i})}{ }^{\mathrm{t}} \mathrm{M}_{(\mathrm{i}+1)}^{-1} \mathbf{r}_{(\mathrm{i})}\right\}$
(5) $\mathbf{p}_{(\mathrm{i}+1)}=\mathrm{M}_{(\mathrm{i}+1)}^{-1} \mathbf{r}_{(\mathrm{i}+1)}+\beta_{(\mathrm{i}+1)} \mathbf{p}_{(\mathrm{i})}$
(6) stop when $\left|\mathbf{r}_{(\mathrm{i}+1)}\right|<\delta$, otherwise go to (2).

