# Traveltime computation and tomography based on the Liouville equation 

Jianliang Qian

TRIP, Rice University, Houston, TX
and
Wichita State University, Wichita, KS
Joint work with Shingyu Leung, UCLA
TRIP Annual Meeting
Friday, January 13, 2006

## Outline

- Overview for traveltime tomography

■ Part I: First-Arrival(FA) based traveltime tomography ■ Mismatching functional and adjoint state methods
■ Fast sweeping for eikonal eqns and adjoint eqns

- Synthetic examples

■ Part II: Multi-arrival(MA) based traveltime tomography

- Paraxial Liouville equations for MAs

■ Mismatching functional and adjoint state methods

- Examples
- Conclusions and future work


## Transmission traveltime tomography



## Ray-tracing based tomography

$\square$ Traveltime between $S$ and $R: t(S, R)=\int_{S}^{R} \frac{d s}{c}$.

- Fermat's principle serves as the foundation: First-Arrivals (FA) based.
- Both ray path and velocity (1/slowness) are unknown.
- Linearize the equation around a given background slowness with an unknown slowness perturbation.
■ Discretize the interested region into pixels of constant velocities.
- Trace rays in the Lagrangian framework.

■ Obtain a linear system linking slowness perturbation with traveltime perturbation.

## Seismic traveltime tomography

- Transmission traveltime tomography estimates wave-speed distribution from acoustic, elastic or electromagnetic first-arrival (FA) traveltime data.
■ Travel-time tomography shares some similarities with medical $X$-ray CT.
■ Geophysical traveltime tomography uses travel-time data between source and receiver to invert for underground wave velocity.
- Seismic tomography usually is formulated as a minimization problem that produces a velocity model minimizing the difference between traveltimes generated by tracing rays through the model and those measured from the data: Lagrangian approaches.


## Traveltime tomography: PDE-based (1)

■ We develop PDE-based Eulerian approaches to traveltime tomography to avoid ray-tracing.

- Part I: FA-based traveltime tomography via eikonal eqns, adjoint state methods and fast eikonal solvers.
■ Sei-Symes'94, '95 formulated FA based traveltime tomography using paraxial eikonal eqns; they only illustrated the feasibility of computing the gradient by using the adjoint state method.
- Our contribution: formulating the problem in terms of the full eikonal eqn, solving the eikonal eqn by fast sweeping methods and designing a new fast sweeping method for the adjoint eqn of the linearized eikonal eqn.


## Traveltime tomography: PDE-based (2)

■ Part II: multi-arrival (MA)-based traveltime tomography via Liouville eqns and adjoint state methods.
■ Our contribution: to our knowledge this is the first Eulerian approach to taking into account all arrivals systematically in the seismic tomography.
■ Delprat-Jannaud and Lailly'95: handling multiple arrivals (MAs) in reflection tomography in the ray-tracing framework, a Lagrangian approach.

## Part I: Eikonal-based tomography

- Traveltimes between a source $S$ and receivers $R$ on the boundary satisfy

$$
c(\mathbf{x})|\nabla T|=1, \quad T\left(\mathbf{x}_{\mathbf{s}}\right)=0 .
$$

$■$ Forward problem: given $c>0$, compute the viscosity solution based FAs from the source to receivers.

- Inverse problem: given both FA measurements on the boundary $\partial \Omega_{p}$ and the location of the point source $\mathbf{x}_{s} \in \partial \Omega_{p}$, invert for the velocity field $c(\mathbf{x})$ inside the domain $\Omega_{p}$.


## FA-based tomography: idea

■ Forward problem: fast eikonal solvers; they are essential for inverse problems.

■ Inverse problem: essential steps.
■ Minimize the mismatching functional between measured and simulated traveltimes.

- Derive the gradient of the mismatching functional and apply an optimization method.
- Linearize the eikonal eqn around a known slowness with an unknown slowness perturbation.
- Solve the eikonal eqn for the viscosity solution: only FAs are used.


## FA-based tomography: formulation

- The mismatching functional (energy),

$$
E(c)=\frac{1}{2} \int_{\partial \Omega_{p}}\left|T-T^{*}\right|^{2},
$$

where $\left.T^{*}\right|_{\partial \Omega_{p}}$ is the data and $\left.T\right|_{\partial \Omega_{p}}$ is the eikonal solution.

- Perturb $c$ by $\epsilon \tilde{c} \Rightarrow$ Perturbation in $T$ by $\epsilon \tilde{T}$ and in $E$ by $\delta E$ :

$$
\begin{aligned}
& \delta E=\epsilon \int_{\partial \Omega_{p}} \tilde{T}\left(T-T^{*}\right)+O\left(\epsilon^{2}\right) . \\
& T_{x} \tilde{T}_{x}+T_{y} \tilde{T}_{y}+T_{z} \tilde{T}_{z}=-\frac{\tilde{c}}{c^{3}} .
\end{aligned}
$$

■ Difficulty: $\delta E$ depends on $\tilde{c}$ implicitly through $\tilde{T}$ and the linearized eikonal equation. Use the adjoint state ${ }_{10}$ method.

## FA-based tomography: adjoint state

■ Introduce $\lambda$ satisfying

$$
\begin{aligned}
& {\left[\left(-T_{x}\right) \lambda\right]_{x}+\left[\left(-T_{y}\right) \lambda\right]_{y}+\left[\left(-T_{z}\right) \lambda\right]_{z}=0,} \\
& (\mathbf{n} \cdot \nabla T) \lambda=T^{*}-T, \text { on } \partial \Omega_{p} .
\end{aligned}
$$

- Impose the BC to back-propagate the time residual into the computational domain.
- Simplify the energy perturbation further,

$$
\frac{\delta E}{\epsilon}=\int_{\Omega_{p}} \frac{\tilde{c} \lambda}{c^{3}} .
$$

■ Choose $\tilde{c}=-\lambda / c^{3} \Rightarrow$ Decrease the energy: $\delta E=-\epsilon \int_{\Omega_{p}} \tilde{c}^{2} \leq 0$.

## FA-based tomography: regularization

■ Enforce

1. $\left.\tilde{c}\right|_{\partial \Omega_{p}}=0$;
2. $c^{k+1}=c^{k}+\epsilon \tilde{c}^{k}$ smooth.

■ The first condition is reasonable as we know the velocity on the boundary.
$\square$ The second condition is a requirement on the smoothness of the update at each step.
$■$ Regularize, $\nu \geq 0$, by using a Sobolev space,

$$
\begin{gathered}
\tilde{c}=-(I-\nu \Delta)^{-1}\left(\frac{\lambda}{c^{3}}\right), \\
\delta E=-\epsilon \int_{\Omega_{p}}\left(\tilde{c}^{2}+\nu|\nabla \tilde{c}|^{2}\right) \leq 0 .
\end{gathered}
$$

## FA-based tomography: multiple data sets (1)

$\square$ A single data set is associated with a single source.
■ Incorporate multiple data sets associated with multiple sources into the formulation.
$■$ Define a new energy for $N$ sets of data:

$$
E^{N}(c)=\frac{1}{2} \sum_{i=1}^{N} \int_{\partial \Omega_{p}}\left|T_{i}-T_{i}^{*}\right|^{2}
$$

where $T_{i}$ are the solutions from the eikonal equation with the corresponding point source condition $T\left(\mathbf{x}_{s}^{i}\right)=0$.

## FA-based tomography: multiple data sets (2)

■ Perturbation in the energy,

$$
\frac{\delta E^{N}}{\epsilon}=\int_{\Omega_{p}} \frac{\tilde{c}}{c^{3}} \sum_{i=1}^{N} \lambda_{i}
$$

where $\lambda_{i}$ is the adjoint state of $T_{i}(i=1, \cdots, N)$ satisfying

$$
\begin{aligned}
& \left\{\left[-\left(T_{i}\right)_{x}\right] \lambda_{i}\right\}_{x}+\left\{\left[-\left(T_{i}\right)_{y}\right] \lambda_{i}\right\}_{y}+\left\{\left[-\left(T_{i}\right)_{z}\right] \lambda_{i}\right\}_{z}=0 \\
& \left(\mathbf{n} \cdot \nabla T_{i}\right) \lambda_{i}=T_{i}^{*}-T_{i}
\end{aligned}
$$

$\square$ To minimize the energy $E^{N}(c)$, choose

$$
\tilde{c}=-(I-\nu \Delta)^{-1}\left(\frac{1}{c^{3}} \sum^{N} \lambda_{i}\right) .
$$

## Fast sweeping for eikonal and adjoint equations

■ Fast eikonal solvers: fast marching (Sethian, ...), ENO-DNO-Postsweeping (Kim-Cook), fast sweeping on Cartesian and triangular meshes (Zhao, Tsai, Cheng, Osher, Kao, Qian, Cecil, Zhang,...); see Engquist-Runborg'03 for more.

- The eikonal eqn is solved by the fast sweeping method (Zhao, Math. Comp'05).
- The adjoint equation for the adjoint state can be solved by fast sweeping methods as well.
■ We have designed a new fast sweeping method for the adjoint eqn. (Leung-Qian'05)


## Fast sweeping for the adjoint equation (1)

$■$ Take the 2-D case to illustrate the idea:

$$
(a \lambda)_{x}+(b \lambda)_{z}=0,
$$

where $a$ and $b$ are given functions of $(x, z)$.
■ Consider a computational cell centered at $\left(x_{i}, z_{j}\right)$ and discretize the equation in conservation form,

$$
\begin{aligned}
& \frac{1}{\Delta x}\left(a_{i+1 / 2, j} \lambda_{i+1 / 2, j}-a_{i-1 / 2, j} \lambda_{i-1 / 2, j}\right) \\
+ & \frac{1}{\Delta z}\left(b_{i, j+1 / 2} \lambda_{i, j+1 / 2}-b_{i, j-1 / 2} \lambda_{i, j-1 / 2}\right)=0
\end{aligned}
$$

## Fast sweeping for the adjoint equation (2)

■ $\lambda$ on the interfaces, $\lambda_{i \pm 1 / 2, j}$ and $\lambda_{i, j \pm 1 / 2}$, determined by the propagation of characteristics, ie, upwinding,

$$
\begin{aligned}
& \frac{1}{\Delta x}\left(\left(a_{i+1 / 2, j}^{+} \lambda_{i, j}+a_{i+1 / 2, j}^{-} \lambda_{i+1, j}\right)\right) \\
- & \frac{1}{\Delta x}\left(\left(a_{i-1 / 2, j}^{+} \lambda_{i-1, j}+a_{i-1 / 2, j}^{-} \lambda_{i, j}\right)\right) \\
+ & \frac{1}{\Delta z}\left(\left(b_{i, j+1 / 2}^{+} \lambda_{i, j}-b_{i, j+1 / 2}^{-} \lambda_{i, j+1}\right)\right) \\
- & \frac{1}{\Delta z}\left(\left(b_{i, j+1 / 2}^{+} \lambda_{i, j-1}-b_{i, j+1 / 2}^{-} \lambda_{i, j}\right)\right)=0
\end{aligned}
$$

where $a_{i+1 / 2, j}^{ \pm}$denote the positive and negative parts of $a_{i+1 / 2, j}$.

## Fast sweeping for the adjoint equation (3)

■ Rewriting as

$$
\begin{aligned}
\alpha= & \left(\frac{a_{i+1 / 2, j}^{+}-a_{i-1 / 2, j}^{-}}{\Delta x}+\frac{b_{i, j+1 / 2}^{+}-b_{i, j-1 / 2}^{-}}{\Delta z}\right) \\
\alpha \lambda_{i, j}= & \frac{a_{i-1 / 2, j}^{+} \lambda_{i-1, j}-a_{i+1 / 2, j}^{-} \lambda_{i+1, j}}{\Delta x} \\
& +\frac{b_{i, j-1 / 2}^{+} \lambda_{i, j-1}-b_{i, j+1 / 2}^{-} \lambda_{i, j+1}}{\Delta z}
\end{aligned}
$$

which gives us an expression to construct a fast sweeping type method.
■ Alternate sweeping strategy applies.

## Other implementation details

- The Poisson eqn is solved by FFT.
- The gradient descent method needs too many iterations.
■ Use the limited memory Broyden, Fletcher, Goldfarb, Shanno (L-BFGS) method: a quasi-Newton optimization method (Byrd, Lu, Nocedal and Zhu'95).
$■$ Ideal illuminations are assumed.


## 2-D Constant (1): 10 sources




## 2-D Constant (2): 10 sources




## 2-D two-Gaussian (1): 10 sources




## 2-D two-Gaussian (2): 10 sources



## 2-D two-Gaussian with $5 \%$ noise (1): 10 sources




## 2-D two-Gaussian with $5 \%$ noise (2): 10 sources




## 3-D Constant: 98 sources



## Marmousi: 20 sources



Figure 1: True synthetic Marmousi vs inversion

## Marmousi: 20 sources



Figure 2: Refined mesh and residual history

## Part II: Liouville-based tomography

■ Question: can we take into account multi-arrivals (MA) to possibly improve resolution?
■ Multi-arrival(MA) based traveltime tomography via Liouville eqns.
$\square$ Liouville + Level set methods + adjoint state methods.
$■$ Our contribution: to our knowledge this is the first Eulerian approach to considering all arrivals systematically in the traveltime tomography.
■ Delprat-Jannaud and Lailly'95: handling multiple arrivals in reflection tomography in the ray-tracing framework: a Lagrangian approach.

## Tomography via Liouville



Figure 3: Use multi-arrivals from received time series via Liouville in phase space

## MA tomography: Liouville

- Liouville based phase space geometrical optics (Engquist and Runborg'03; many others).
- Paraxial Liouville eqns are based on paraxial eikonals and level sets (Leung-Qian-Osher'04):

$$
\begin{aligned}
& \frac{\partial \tau}{\partial z}=\sqrt{\max \left(\frac{1}{c^{2}}-\left(\frac{\partial \tau}{\partial x}\right)^{2}, \frac{\cos ^{2} \theta_{\max }}{c^{2}}\right)}, \\
& \phi_{z}+u \phi_{x}+v \phi_{\theta}=0, \\
& T_{z}+u T_{x}+v T_{\theta}=\frac{1}{c \cos \theta},
\end{aligned}
$$

where $\mathbf{u}=(u, v)=\left(\tan \theta, m_{z} \tan \theta-m_{x}\right)$,
$m=m(c)=\log c ; \phi$ and $T$ are the level set and traveltime functions in the reduced phase space $\Omega=\left\{(x, \theta): x_{\min } \leq x \leq x_{\max },-\theta_{\max } \leq \theta \leq \theta_{\max }\right\}$.

## MA tomography: complete data

$\square$ I.B.C. (n being the outward normal of $\partial \Omega$ ):

$$
\begin{aligned}
\phi\left(z_{0}, \cdot, \cdot\right) & =x \\
\left.\phi(z, \cdot, \cdot)\right|_{\partial \Omega} & =\left\{\begin{array}{cl}
\phi^{*} & \text { if }(\mathbf{u} \cdot \mathbf{n})<0 \\
\text { no b.c. needed } & \text { if }(\mathbf{u} \cdot \mathbf{n}) \geq 0
\end{array}\right. \\
T\left(z_{0}, \cdot, \cdot\right) & =0 \\
\left.T(z, \cdot, \cdot)\right|_{\partial \Omega} & =\left\{\begin{array}{cl}
T^{*} & \text { if }(\mathbf{u} \cdot \mathbf{n})<0 \\
\text { no b.c. needed } & \text { if }(\mathbf{u} \cdot \mathbf{n}) \geq 0
\end{array}\right.
\end{aligned}
$$

■ Use $(\cdot)^{*}$ to denote the measured value on the outflow boundary of $\partial \Omega$ and on the final level $z=z_{f}$.
■ Such measurements can be picked by suitably pairing as in Delprat-Jannaud and Lailly'95.

## MA tomography: energy

$■ \tilde{\Omega}=\Omega \times\left(z_{0}, z_{f}\right) ; \Omega_{p}=\left(x_{\min }, x_{\max }\right) \times\left(z_{0}, z_{f}\right)$.
■ Data: $\left.\phi^{*}(z, \cdot, \cdot)\right|_{\partial \Omega}$ and $\left.T^{*}(z, \cdot, \cdot)\right|_{\partial \Omega}$ on the outflow boundary; $\phi^{*}\left(z_{f}, \cdot, \cdot\right)$ and $T^{*}\left(z_{f}, \cdot, \cdot\right)$ at $z=z_{f} ;\left.m\right|_{\partial \Omega_{p}}$.
■ Minimize the energy:

$$
\begin{aligned}
& E(m)=\left.\frac{1}{2} \int_{\Omega}\left(\phi-\phi^{*}\right)^{2}\right|_{z=z_{f}}+\frac{1}{2} \int_{z} \int_{\partial \Omega}(\mathbf{u} \cdot \mathbf{n})\left(\phi-\phi^{*}\right)^{2} \\
& \left.+\left.\frac{\beta}{2} \int_{\Omega}\left(T-T^{*}\right)^{2}\right|_{z=z_{f}}+\frac{\beta}{2} \int_{z} \int_{\partial \Omega} \mathbf{u} \cdot \mathbf{n}\right)\left(T-T^{*}\right)^{2} .
\end{aligned}
$$

- Derive the gradient of the nonlinear functional by the adjoint state method.
- Linearize the Liouville eqns and the energy around a known background slowness with an unknown slowness perturbation.


## MA tomography: linearization

■ Perturb $m$ by $\epsilon \tilde{m}$; changes in $\phi$ and $T$ by $\epsilon \tilde{\phi}$ and $\epsilon \tilde{T}$ :

$$
\begin{aligned}
& \tilde{\phi}_{z}+u \tilde{\phi}_{x}+v \tilde{\phi}_{\theta}=\left[\tilde{m}_{x}-\tilde{m}_{z} \tan \theta\right] \phi_{\theta}, \\
& \tilde{T}_{z}+u \tilde{T}_{x}+v \tilde{T}_{\theta}=\left[\tilde{m}_{x}-\tilde{m}_{z} \tan \theta\right] T_{\theta}-\frac{\tilde{m}}{c \cos \theta} .
\end{aligned}
$$

■ Perturbation in energy:

$$
\delta E=E(m+\epsilon \tilde{m})-E(m),
$$

where $\tilde{\mathbf{u}}=(0, \tilde{v})=\left(0, \tilde{m}_{z} \tan \theta-\tilde{m}_{x}\right)$.

## MA tomography: adjoints

■ Choose $\lambda_{1}$ and $\lambda_{2}$ such that

$$
\begin{aligned}
& \left(\lambda_{1}\right)_{z}+\left(u \lambda_{1}\right)_{x}+\left(v \lambda_{1}\right)_{\theta}=0 \\
& \left(\lambda_{2}\right)_{z}+\left(u \lambda_{2}\right)_{x}+\left(v \lambda_{2}\right)_{\theta}=0
\end{aligned}
$$

with the "initial" conditions on $z=z_{f}$,

$$
\begin{aligned}
& \lambda_{1}\left(z=z_{f}\right)=\phi^{*}-\phi \\
& \lambda_{2}\left(z=z_{f}\right)=T^{*}-T .
\end{aligned}
$$

■ With boundary conditions ...

## MA tomography: gradient

■ Boundary conditions

$$
\begin{aligned}
& \left.\lambda_{1}\right|_{\partial \Omega}=\left\{\begin{array}{cc}
\phi^{*}-\phi & \text { if }(\mathbf{u} \cdot \mathbf{n})>0 \\
\text { no b.c. needed } & \text { if }(\mathbf{u} \cdot \mathbf{n}) \leq 0
\end{array}\right. \\
& \left.\lambda_{2}\right|_{\partial \Omega}=\left\{\begin{array}{cc}
T^{*}-T & \text { if }(\mathbf{u} \cdot \mathbf{n})>0 \\
\text { no b.c. needed } & \text { if }(\mathbf{u} \cdot \mathbf{n}) \leq 0
\end{array}\right.
\end{aligned}
$$

■ Perturbation in energy ( $f_{i}, i=1: 4$ computable):

$$
\delta E=\epsilon \int_{\Omega_{p}} \tilde{m}\left\{\left(f_{1}\right)_{x}-\left(f_{2}\right)_{z}+\frac{\beta}{c} f_{3}+f_{4}\right\} .
$$

## MA tomography: regularization

■ To decrease the energy, choose by Tikhonov regularization

$$
\tilde{m}=-(I-\nu \Delta)^{-1} g
$$

where

$$
\begin{gathered}
g=\left(f_{1}\right)_{x}-\left(f_{2}\right)_{z}+\frac{\beta}{c} f_{3}+f_{4} . \\
\delta E=\epsilon \int_{\Omega_{p}} \tilde{m} g=-\epsilon \int_{\Omega_{p}}\left(|\tilde{m}|^{2}+\nu|\nabla \tilde{m}|^{2}\right) \leq 0 .
\end{gathered}
$$

■ Implementations: HJ-WENO, HJ-Central-WENO, FFT and gradient descent methods.

## Constant vel.




## Waveguide vel.: (1)




## Waveguide vel.: (2)




## 2-D two-Gaussian vel.: (1)




## 2-D two-Gaussian vel.: (2)




## Two-Gaussian vel. with noisy data




## Two-Gaussian: FA vs MA




Figure 4: (a): FA with 10 sources; (b): MA.

## MA tomography: incomplete data

■ Only have the measurement on the final level $z=z_{f}$.

- Data: $\Gamma\left(z_{f}\right)=\left\{\phi\left(x, \theta, z_{f}\right), T\left(x, \theta, z_{f}\right):(x, \theta) \in \Omega\right\}$.
- Paraxial assumption implies that relevant rays will not touch the boundary of the domain $\tilde{\Omega}=\Omega \times\left(0, z_{f}\right)$.
- Ignore the contribution from inflows in the energy.
- Simplify the energy:

$$
\begin{aligned}
E(m)= & \frac{1}{2} \int_{\Omega}\left(\phi-\phi^{*}\right)^{2} \delta\left(\Gamma\left(z_{f}\right)\right)+ \\
& +\frac{\beta}{2} \int_{\Omega}\left(T-T^{*}\right)^{2} \delta\left(\Gamma\left(z_{f}\right)\right)
\end{aligned}
$$

- Simplify the gradient as well.


## Conclusion and future work

■ Developed PDE-based approaches to traveltime tomography: FAs and MAs.
$■$ Validated accuracy and efficiency of the approaches under ideal illuminations.
■ Future work consists of

- taking into account the partial illumination of the computational domain (Joint with TRIP);
$\square$ formulating FA-based reflective traveltime tomography (Leung-Qian'05)
- formulating MA-based high resolution reflective traveltime tomography

