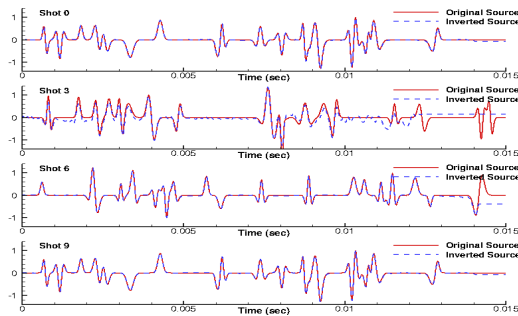
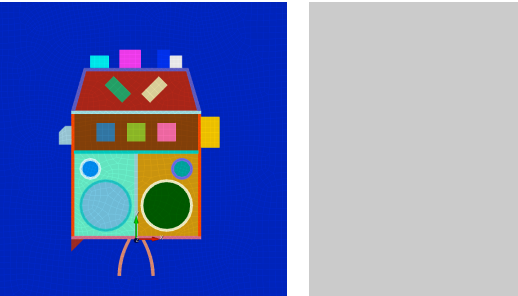




Large-Scale Optimization for Non-Invasive Testing with Discontinuous Galerkin Methods

Curtis Ober*, Thomas Smith,
Bart van Bloemen Waanders, and Scott Collis



*Exceptional
service
in the
national
interest*



Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000. SAND NO. 2011-XXXXP

Non-Invasive Testing

- ... determine the characteristics engineering systems without disassembling or damaging them.
- Source Inversion
 - Interested in mimicing operational conditions within an experimental setup to test conditions throughout the system
 - Direct Field Acoustic Testing – DFAT
 - Acoustic testing of aerospace structures
 - Use an array of acoustic drivers
- Material inversion
 - Characterize material properties
 - Aging, cracks
 - Miss-assembly
 - DFAT and ultrasonic testing

Direct Field Acoustic Testing



http://en.wikipedia.org/wiki/Direct_Field_Acoustic_Testing

Constrained Optimization Problem

$$\min_{\Phi} J(\mathbf{U}, \Phi) \equiv \frac{1}{2} \sum_{s=1}^{N_s} \sum_{r=1}^{N_r} \int_Q \xi_{s,r}(\mathbf{x}) \left\| \mathbf{R}(\mathbf{U}_s - \hat{\mathbf{U}}_s) \right\|^2 d\mathbf{Q} + \frac{\beta}{2} \int_{\Omega} \left\| \mathbf{R}(\Phi) \right\|^2 d\Omega$$

- Subject to the acoustic wave equation

$$\frac{\partial p}{\partial t} + \kappa \frac{\partial v_i}{\partial x_i} = -\frac{1}{3} \frac{\partial m_{ii}^{iso}}{\partial t} \quad \text{in } \Omega \times (0, T]$$

$$\rho \frac{\partial v_i}{\partial t} + \frac{\partial p}{\partial x_i} = f_i + \frac{\partial m_{ij}^{dev}}{\partial x_j} \quad \text{in } \Omega \times (0, T]$$

$$p(\mathbf{x}, 0) = 0 \quad \text{for } \mathbf{x} \in \Omega$$

$$v_i(\mathbf{x}, 0) = 0 \quad \text{for } \mathbf{x} \in \Omega$$

$$\mathbf{U} = (p, v_i)^T$$

$$\kappa = \rho c^2 - \text{bulk modulus}$$

$$\rho = \text{mass density}$$

$$c = \text{wave speed}$$

$$f_i = \text{force density}$$

$$m_{ij} = m_{ij}^{iso} + m_{ij}^{dev} - \text{moment density tensor}$$

$$m_{ij}^{iso} \equiv \frac{1}{3} m_{kk} \delta_{ij}$$

$$\Omega = \text{computational domain}$$

$$T = \text{time horizon}$$

$$\xi_{s,r} = \text{receiver spatial kernel for shot } s$$

$$\mathbf{R} = \text{selection operator}$$

$$\Phi = \text{optimization parameters}$$

Discontinuous Galerkin

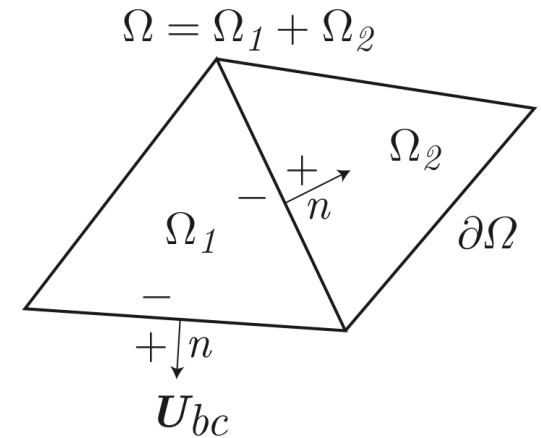
Strong form:

$$\mathbf{U}_{,t} + \mathbf{F}_{i,i} = \mathbf{S}, \quad \text{in } \Omega$$

$$\mathbf{U}(x, 0) = \mathbf{U}_0(x) \quad \text{at } t = 0$$

and appropriate boundary conditions on $\partial\Omega$.

Partition Ω into N subdomains Ω_e .



$$\int_{\Omega_e} (\mathbf{W}^T \mathbf{U}_{,t} - \mathbf{W}_{,i}^T \mathbf{F}_i) d\Omega + \int_{\partial\Omega_e} \mathbf{W}^T \mathbf{F}_n d\Gamma = \int_{\Omega_e} \mathbf{W}^T \mathbf{S} d\Omega$$

Introduce numerical fluxes $\mathbf{F}_n(\mathbf{U}) \rightarrow \hat{\mathbf{F}}_n(\mathbf{U}^-, \mathbf{U}^+)$ and sum over all elements

$$\sum_{e=1}^{N_e} \int_{\Omega_e} (\mathbf{W}^T \mathbf{U}_{,t} - \mathbf{W}_{,i}^T \mathbf{F}_i - \mathbf{W}^T \mathbf{S}) d\Omega + \int_{\partial\Omega_e} \mathbf{W}^T \hat{\mathbf{F}}_n d\Gamma = 0$$

$$\sum_{e=1}^{N_e} \int_{\Omega_e} (\mathbf{W}^T \mathbf{U}_{,t} + \mathbf{W}^T \mathbf{F}_{i,i} - \mathbf{W}^T \mathbf{S}) d\Omega + \int_{\partial\Omega_e} \mathbf{W}^T (\hat{\mathbf{F}}_n - \mathbf{F}_n) d\Gamma = 0$$

for all $\mathbf{W} \in \mathcal{V}$.

DGM Software

- Variety of physics
 - In- & compressible Euler, compressible Navier-Stokes (with LES)
 - Darcy, Helmholtz, [Wave equation](#)
- High-order DG on unstructured meshes (low dispersion)
 - Modal elements: Line, Quad, [Tri](#), [Hex](#)
 - Nodal elements: Line, Quad, Tri, Hex, Tet
 - Spectral Elements: Line, Quad, Hex
 - Curved elements and [hybrid meshes](#)
 - [Variable-order polynomial representation](#) (For both [solution](#) and [media](#))
 - [Local polynomial](#) and mesh refinement
 - Various flux functions (Lax-Friedrichs, Steger-Warming, [Riemann](#))
- Range of explicit and implicit time integrators
 - Forward & Backward Euler, Trapezoidal, [4th Order Runge-Kutta](#) (low dispersion)
- Designed for adjoint-based optimization
 - [ROL](#), PEOpt, Dakota, MOOCHO, Aristos
 - Steady-state and [transient with check pointing](#)

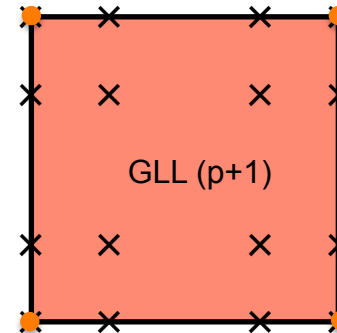
Modal vs. Nodal vs. Spectral

	Modal (Karniadakis & Sherwin, 2005, Collis, 2002)	Nodal (Hesthaven & Warburton, 2000; Kaser & Dumbser, 2006, 2008)	Spectral (Karniadakis & Sherwin, 2005)
Elements	Line, Tri, Quad, Hex	Line, Tri, Quad, Hex, Tet	Line, Quad, Hex
DoFs	coefficients of polynomial bases	nodes of the Lagrange polynomials	GLL nodes
Interpolation	transform/Lagrange	Lagrange	Lagrange sampled at Legendre zeros
Mass term integration	constant for affine elements, Gauss quadrature for non-affine	orthogonal bases – exact integration for affine elements, Gauss quadrature for non-affine	diagonal for affine and non- affine elements
Volume Integration	Gauss-Lobatto quadrature $Q \geq P+2$; exact integration	orthogonal bases – exact analytic	Gauss-Lobatto quadrature, $Q=P+1$
Surface integration/ Flux data	interpolate on face, Gauss quadrature $Q_{\text{edg}}=P+1$	data is native to face – no interpolation- exact integration	no interpolation for constant P, face interpolation for non- const. P
Media	variable within element	constant within element	variable within element
Element Jacobian	variable within element	constant over element	variable within element
Non-linear terms	increase number of quadrature points GLL	filter or use quadrature	filter high modes (de-alias)

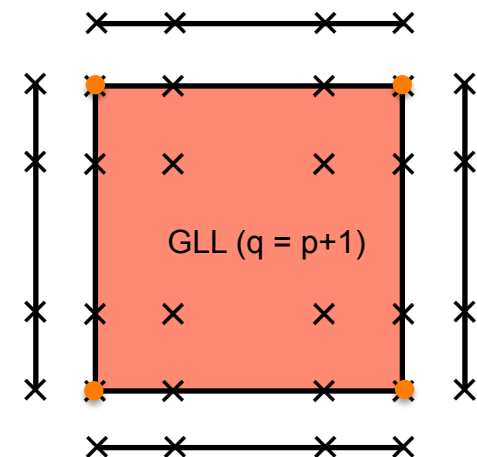
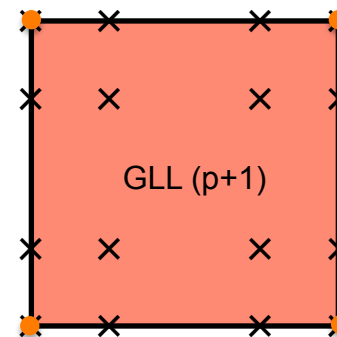
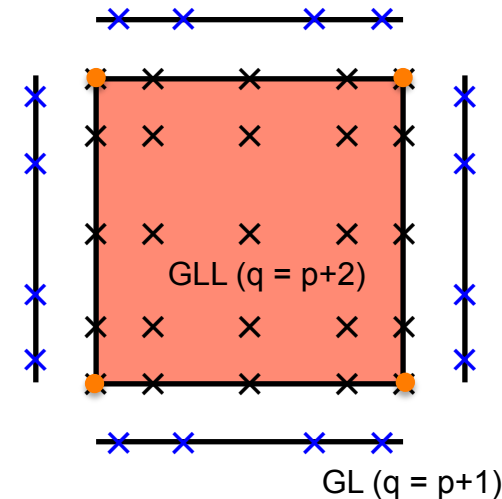
Modal and Spectral Elements

- Modal (**more accurate**)
 - Uses Legendre basis (modes)
 - Uses quadrature for all integrals
 - Can exactly integrate higher-order polynomial products by increasing quadrature ($q \geq p+2$)
 - Requires interpolation from nodes to quad pts.
 - For affine elements, mass matrix is constant and easily inverted and stored.
 - For non-affine elements, mass matrix is dense and needs inverting every time step and stage.
- In Common
 - Uses tensor-products of orthogonal polynomials
 - Support spatially variable polynomial order
 - Variable media, nonlinearities, & non-affine elements produce higher-order polynomial products
- Spectral (**less accurate; less expensive**)
 - Uses Lagrange basis on optimal node distributions
 - Under integrates higher-order polynomial products because of fixed quadrature ($q = p+1$)
 - May need to resort to modal or inexact quadrature + filtering for higher-order polynomial products
 - No interpolation required.
 - For affine & non-affine elements, mass matrix is diagonal and easily inverted.

Node Pts.
(solution)



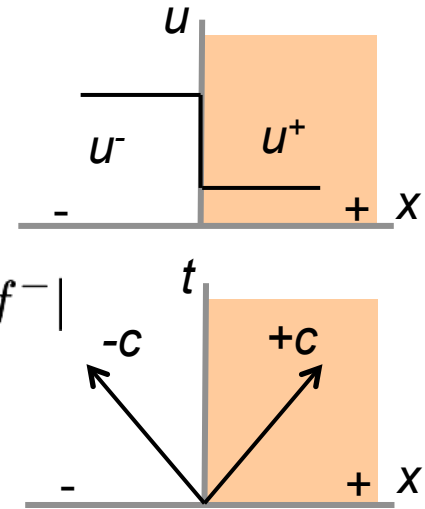
Quadrature Pts.
(integration)



Numerical Fluxes

- Riemann Flux (Exact flux)

- Conservative form $u_{,t} + f_{,x} = 0$ not $u_{,t} + c u_{,x} = 0$
- Rankine-Hugoniot Jump Conditions $c|u^+ - u^-| = |f^+ - f^-|$
- Entropy Conditions



- Flux, flux Jacobian, and eigenvalues are

$$\mathbf{F}_n = (\mathbf{A}_n \mathbf{U})$$

$$\mathbf{A}_i \equiv \frac{\partial \mathbf{F}_i}{\partial \mathbf{U}}$$

$$\mathbf{\Lambda} = \text{diag} \{ \lambda_1, \dots, \lambda_N \}$$

$$= \text{diag} \{ \text{eigen}(\mathbf{A}_n) \}$$

- Lax-Friedrich Flux

$$\hat{\mathbf{F}}_n(\mathbf{U}^-, \mathbf{U}^+) = \frac{1}{2} [\mathbf{F}_n^- + \mathbf{F}_n^+ + \xi (\mathbf{U}^- - \mathbf{U}^+)]$$

$$\xi = \max |\lambda_i|$$

- Steger-Warming Flux (Flux-Vector Splitting)

$$\mathbf{A}_n = \mathbf{A}^+ + \mathbf{A}^- = \mathbf{T} \mathbf{\Lambda}^+ \mathbf{T}^{-1} + \mathbf{T} \mathbf{\Lambda}^- \mathbf{T}^{-1}$$

$$\mathbf{\Lambda}^\pm = (\mathbf{\Lambda} \pm |\mathbf{\Lambda}|) / 2$$

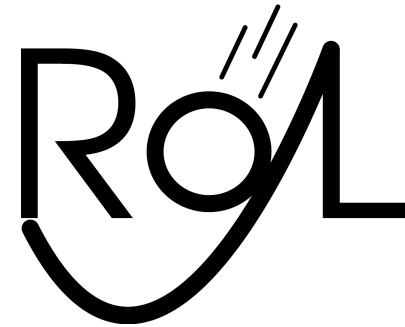
$$\hat{\mathbf{F}}_n = \frac{1}{2} [\mathbf{A}_n^- \mathbf{U}^- + \mathbf{A}_n^- \mathbf{U}^+ + |\mathbf{A}_n| (\mathbf{U}^- - \mathbf{U}^+)]$$

$$|\mathbf{A}| = \mathbf{T} |\mathbf{\Lambda}| \mathbf{T}^{-1}$$

Optimization Software



- Rapid Optimization Library (ROL)
 - Release within Trilinos in October 2014
 - Rewrite and consolidation of existing tools
 - PEOpt, Aristos, Moocho, Optipack
 - Lead developers: Drew Kouri (primary) and Denis Ridzal
 - Unconstrained optimization
 - Gradient descent, quasi-Newton, nonlinear CG, inexact Newton (FD Hessvecs), with line searches and trust regions.
 - Inequality constraints
 - Box constraints using projected gradient and projected Newton methods



ROL: Methods – FD Hessvecs

$$\min_z J(z)$$

- Goal: Obtain near quadratic convergence from Newton-CG with finite difference Hessian-times-a-vector
 - Set $H(z, v, t) = [\nabla J(z + tv) - \nabla J(z)] / t$
 - Apply inexact CG to Newton system: $H(z_k, s, t) = -\nabla J(z_k)$
 - At j^{th} iteration of inexact CG require:
$$\|H(z_k, v_j, t_j) - \nabla^2 J(z_k)v_j\| \leq c_m \varepsilon_k / \|r_{j-1}\|$$
 - Constant depending on max # CG iterations, c_m
 - Previous inexact G residual, ε_k
 - Tolerance governed by inexact Newton's method, r_{j-1}

ROL: Methods – FD Hessvecs

■ Convergence

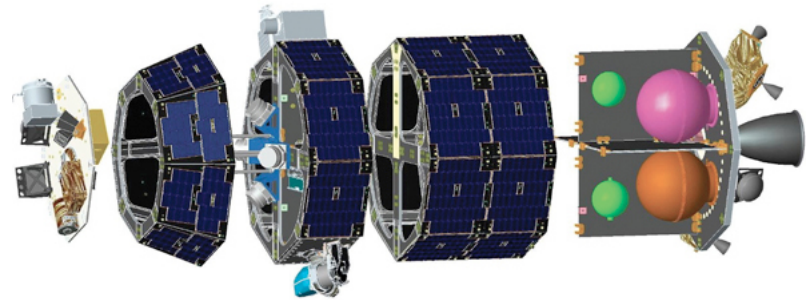
- Standard assumptions for Newton's
 - If $\nabla^2 J(z)$ is Lipschitz then $\|H(z, v, t) - \nabla^2 J(z)v\| = \mathcal{O}(t)$
- Error between inexact and true CG residuals is ε_k
 - Simoncini and Szyld 2002
- Inexact Newton's Methods: Can satisfy Krylov tolerances which ensure superlinear or quadratic convergence.

■ Notes

- FD Hessvecs require an additional gradient computation per CG iteration
- $t_j = \varepsilon_k / (\|v_j\| \|r_{j-1}\|)$ works well in practice.
- Use line search to globalize new step.

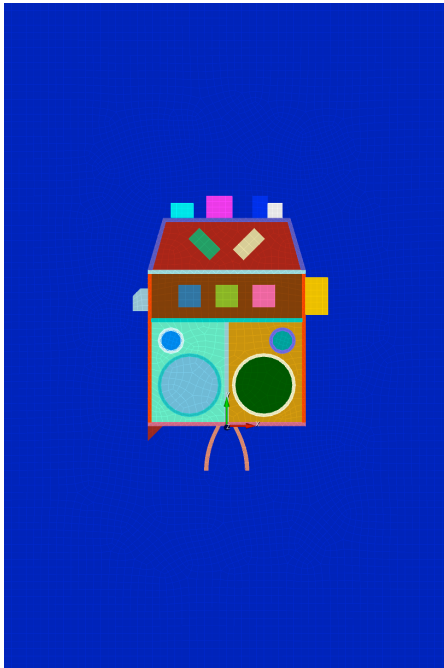
Mock Satellite

- Modeling structure after
 - NASA Ames Lunar Atmosphere Dust and Environment Explorer (LADEE)
 - Crude 2D representation to demonstrate capabilities

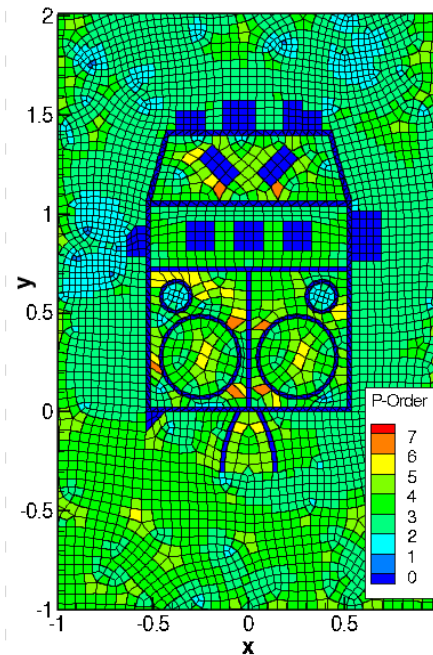


<http://machinedesign.com/cad/software-lets-spacecraft-carry-heavier-loads>

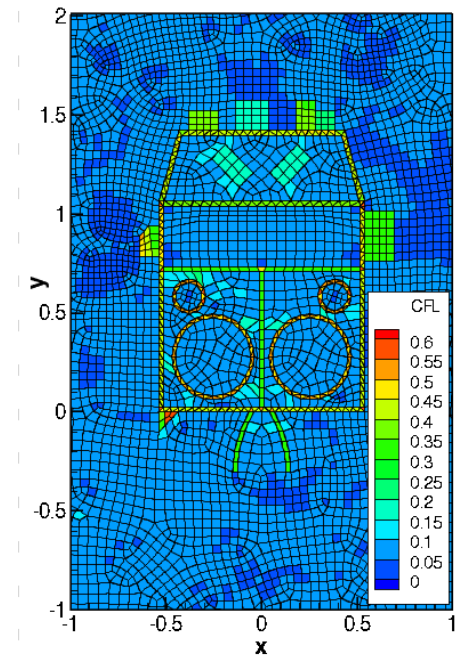
Mesh



Polynomial Order

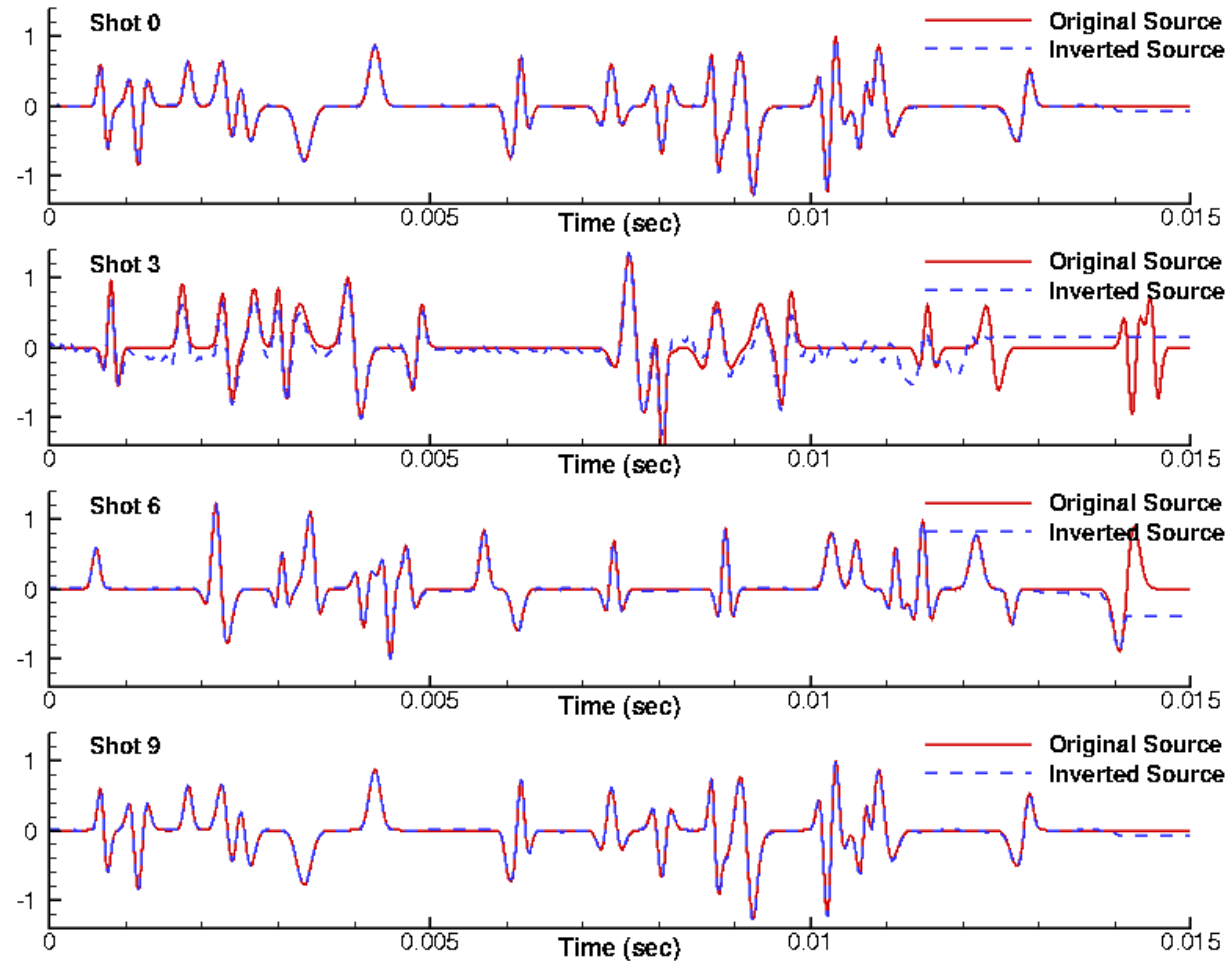
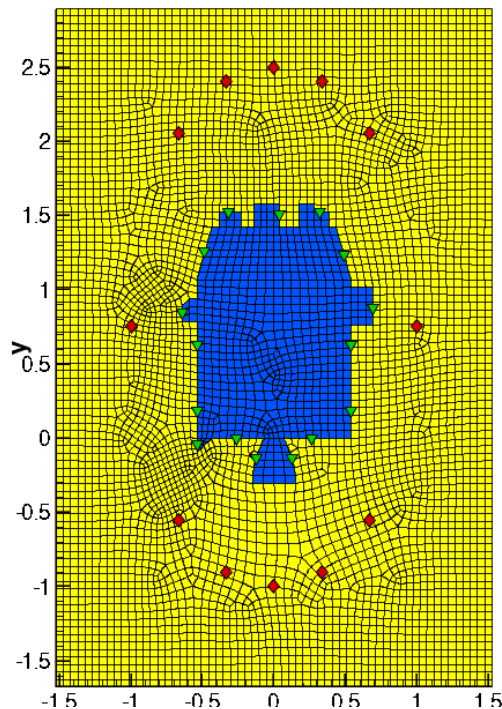


CFL



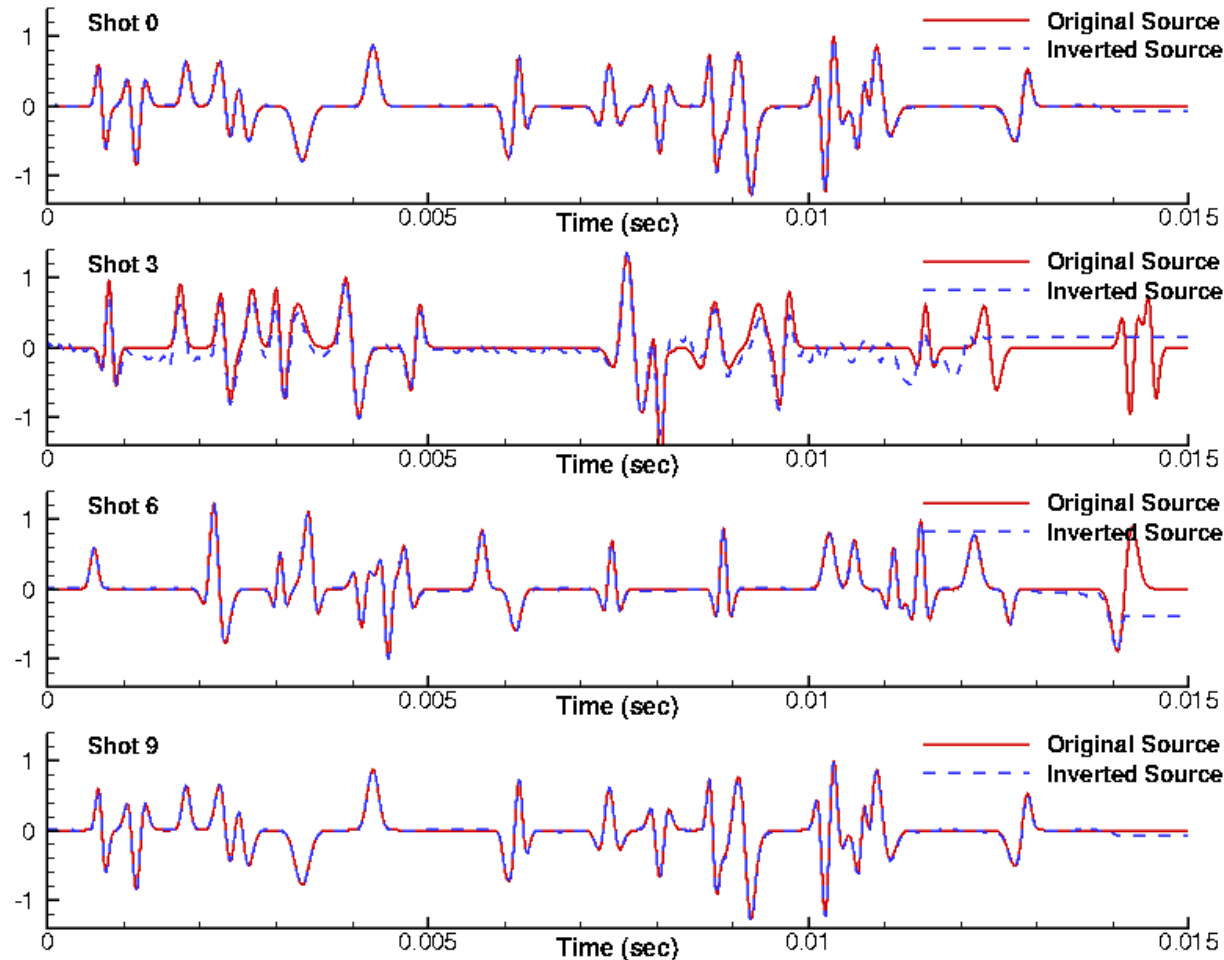
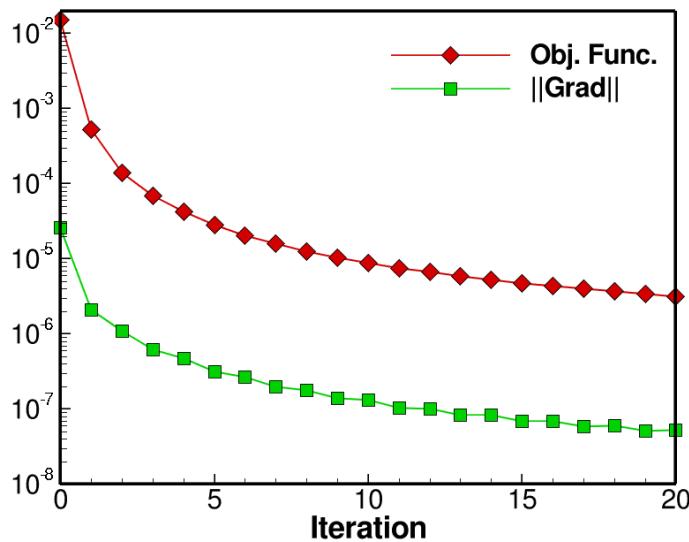
2D Source Inversion

- 12 sources
- Inversion crime
- Supershot



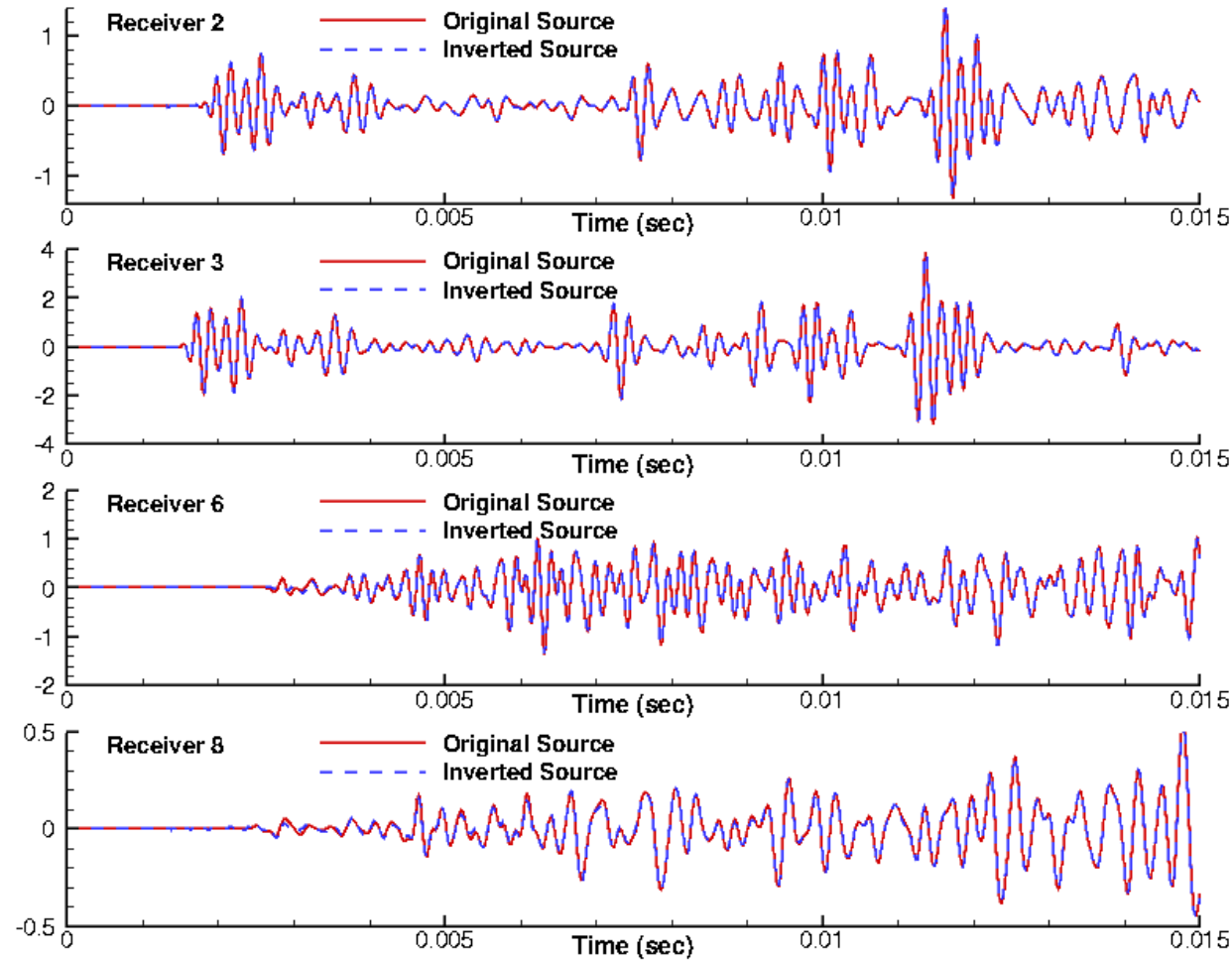
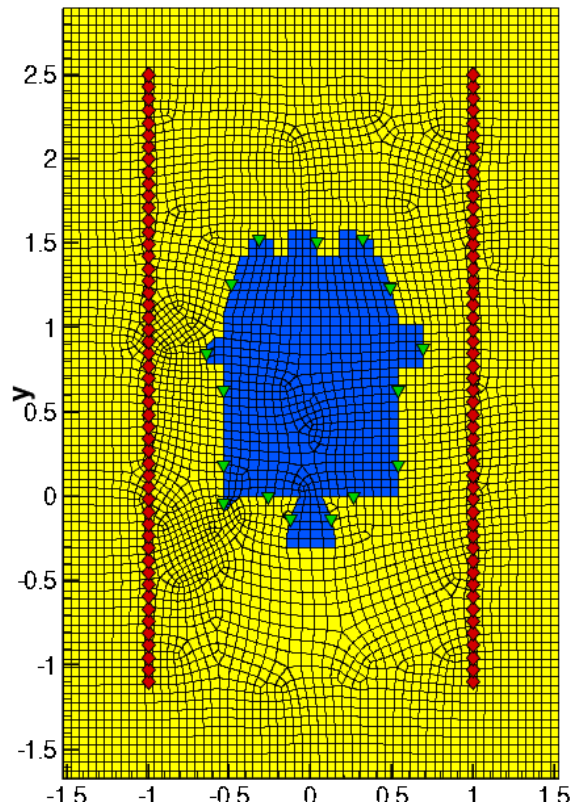
2D Source Inversion

- 12 sources
- Inversion crime
- Supershot



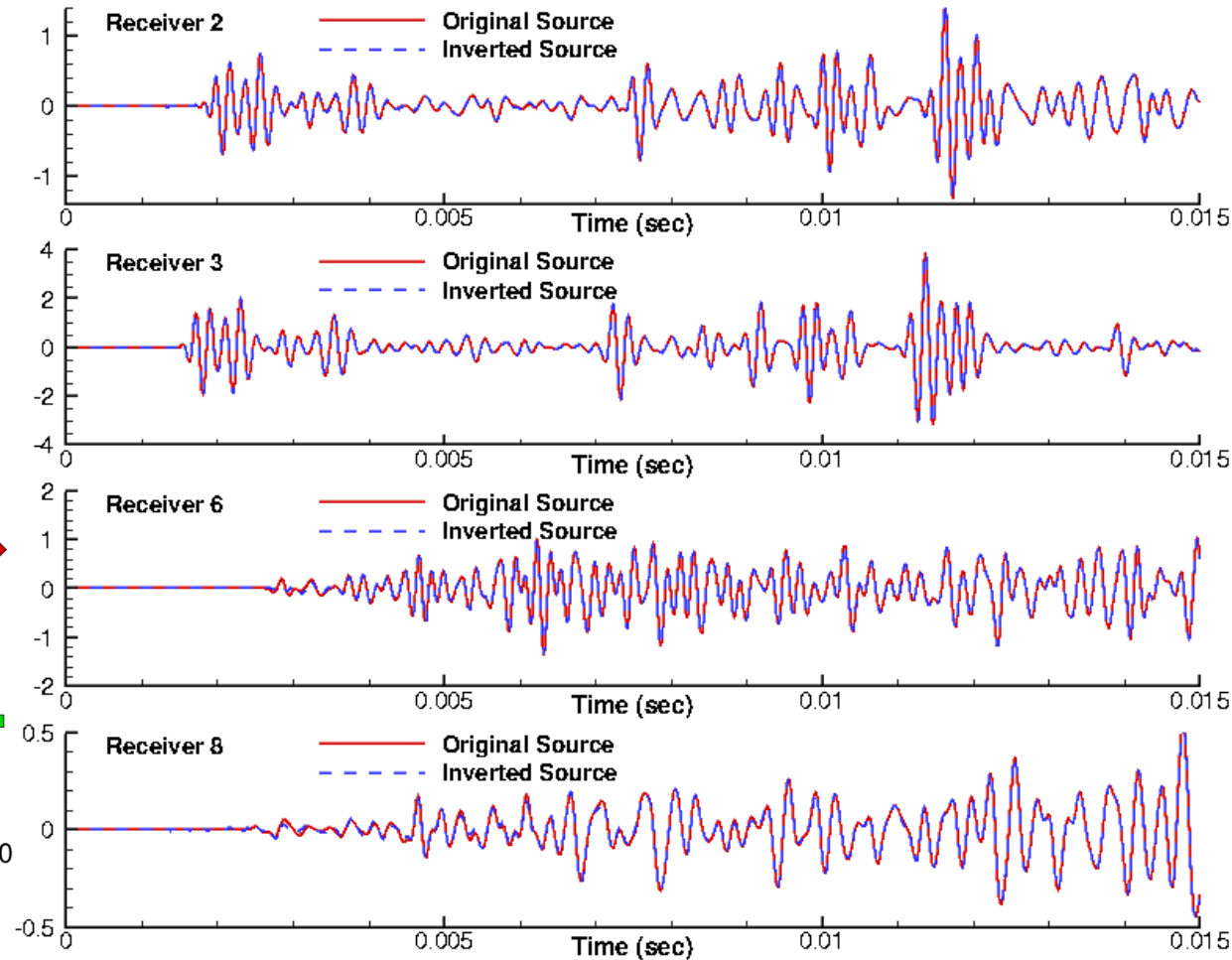
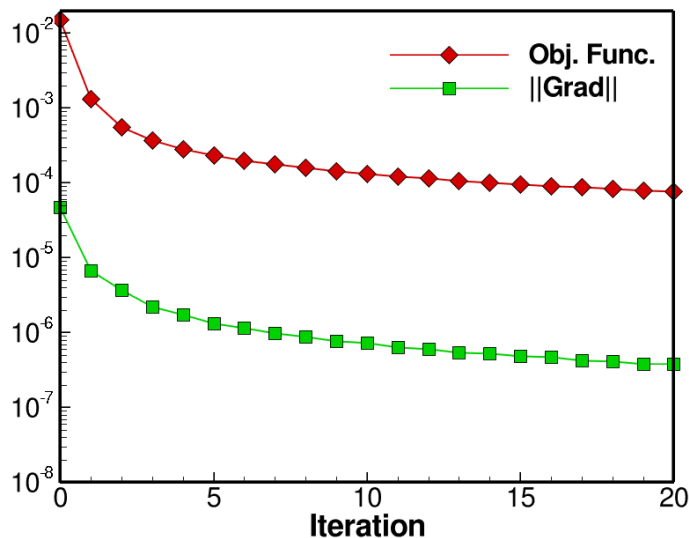
2D Source Inversion

- 102 sources
- Supershot



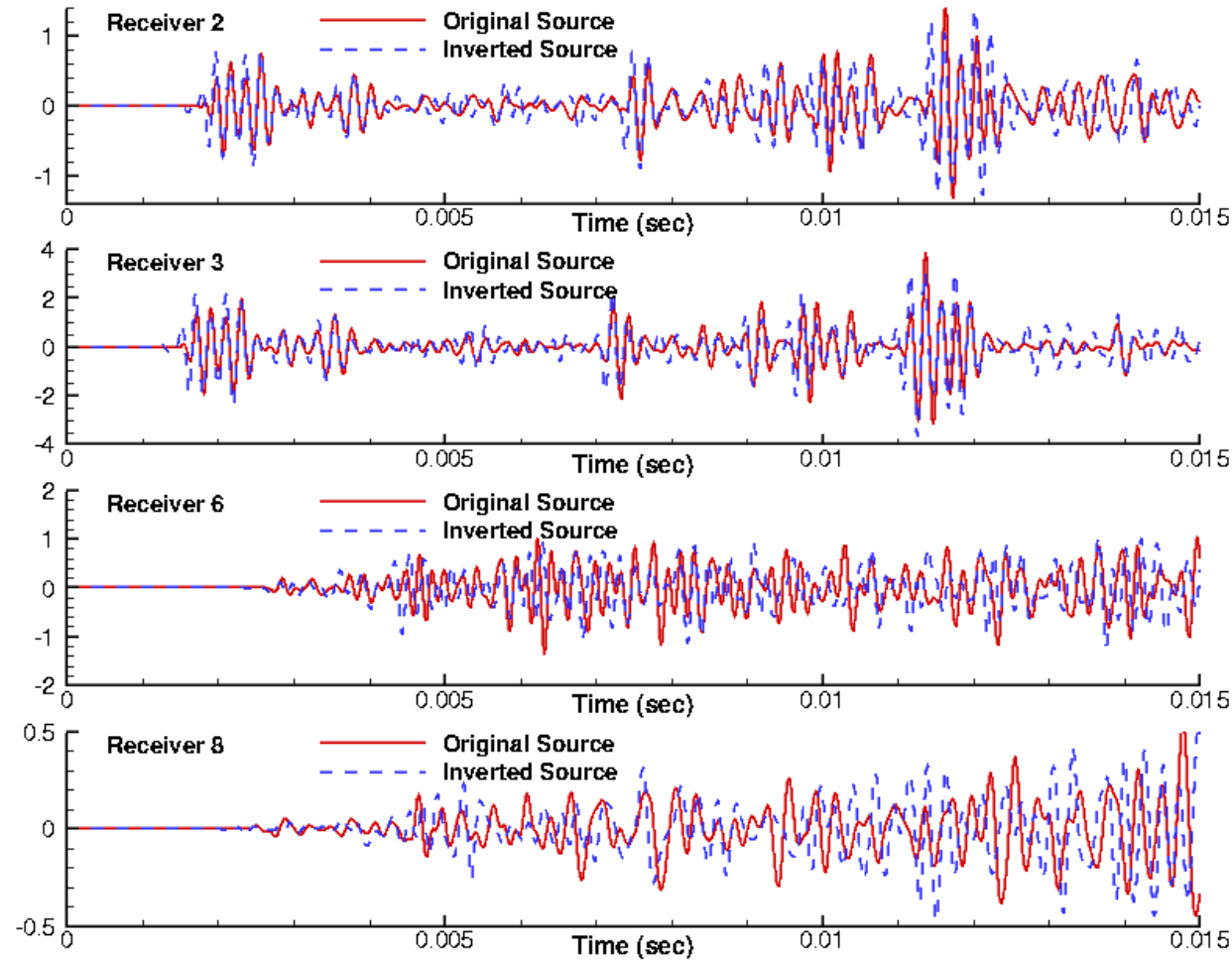
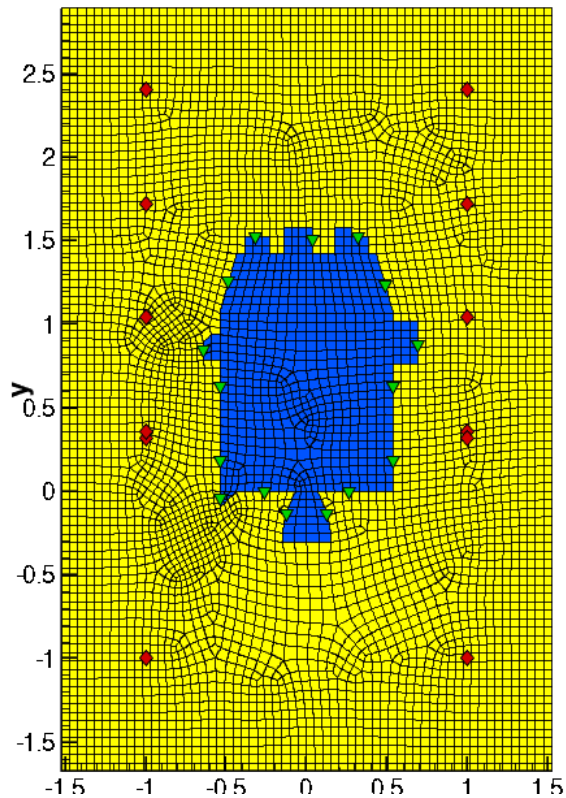
2D Source Inversion

- 102 sources
- Supershot



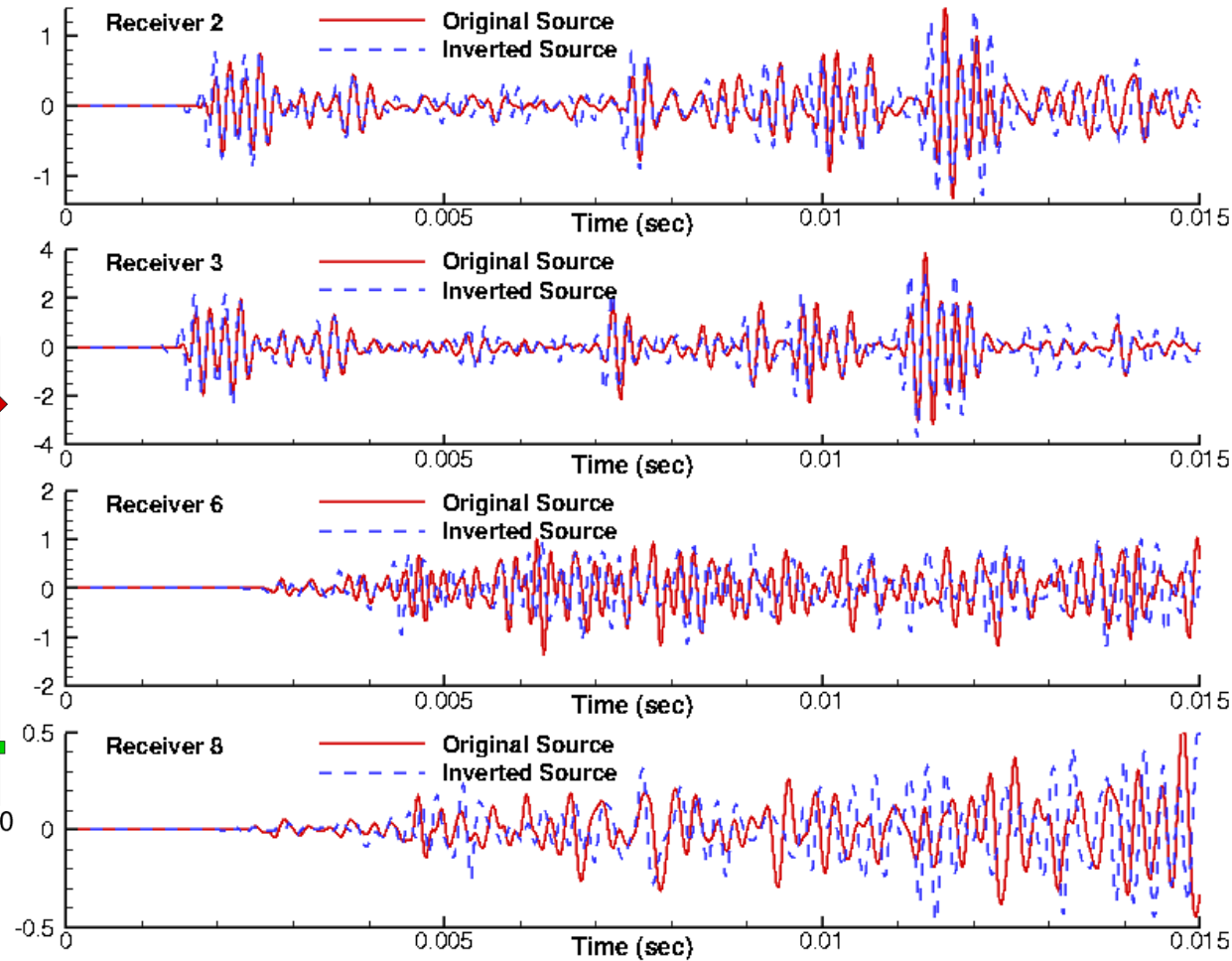
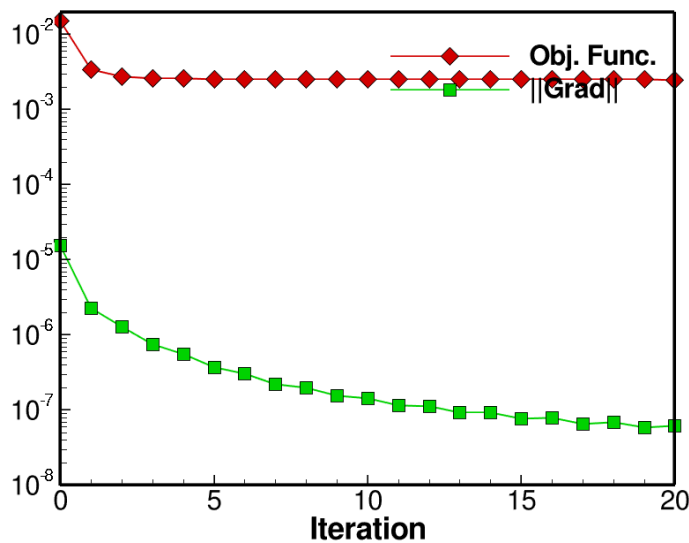
2D Source Inversion

- 12 sources
- Supershot



2D Source Inversion

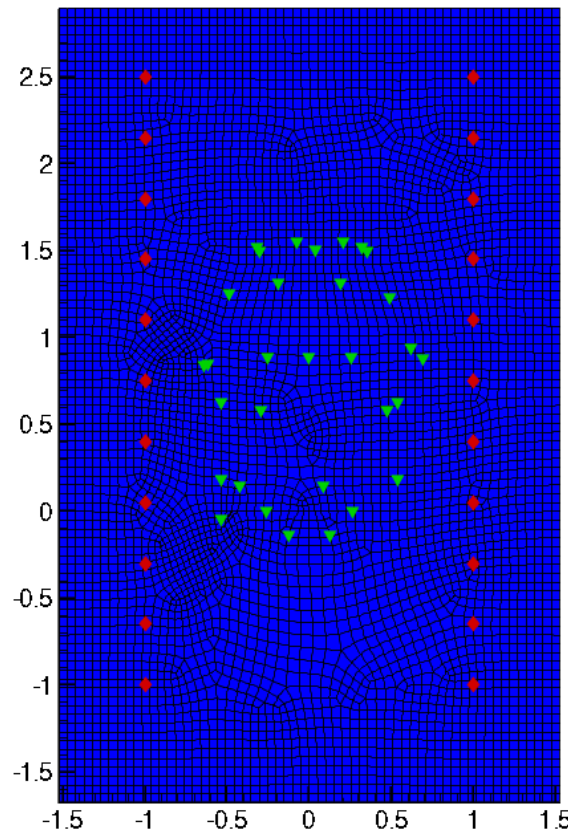
- 12 sources
- Supershot



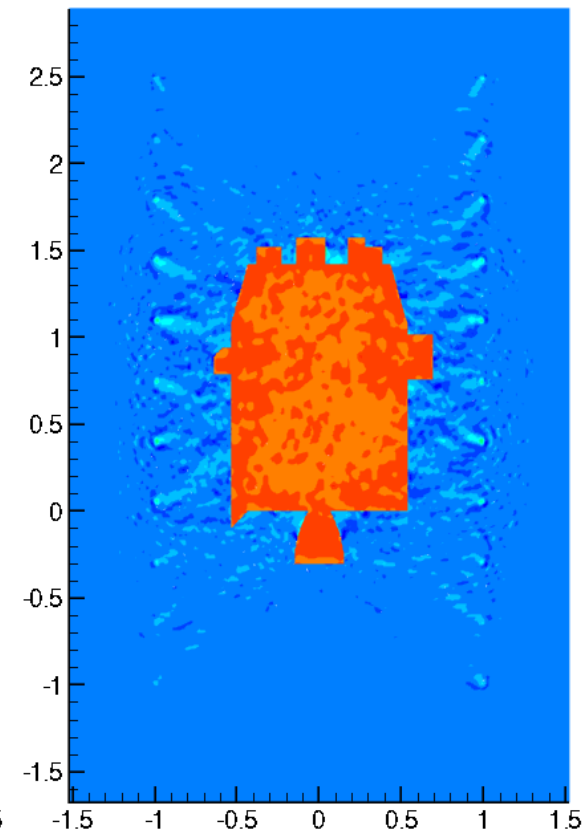
2D Material Inversion

- 22 individual sources
- 31 receivers
 - 16 on surface
 - 15 on the interior
- Sim time $T = 0.015$ sec.
- Constant $p = 4$
- Absorbing BCs
- After 11 iterations

Src & Rec Locations



Inverted Media Results



Summary

- Demonstration of DG inversion for non-invasive testing
 - Low dispersion properties allows coarser mesh
 - Variable p-order mesh allows matching order to wavelengths for every element size
 - 2D hybrid mesh using triangles and quadrilaterals
- Source inversion to mimic launch conditions
 - Open question whether there is enough speakers
- Material inversion
 - Initial work promising