



Inverse Structural Acoustic Source and Material Identification in a Massively Parallel Finite Element Framework

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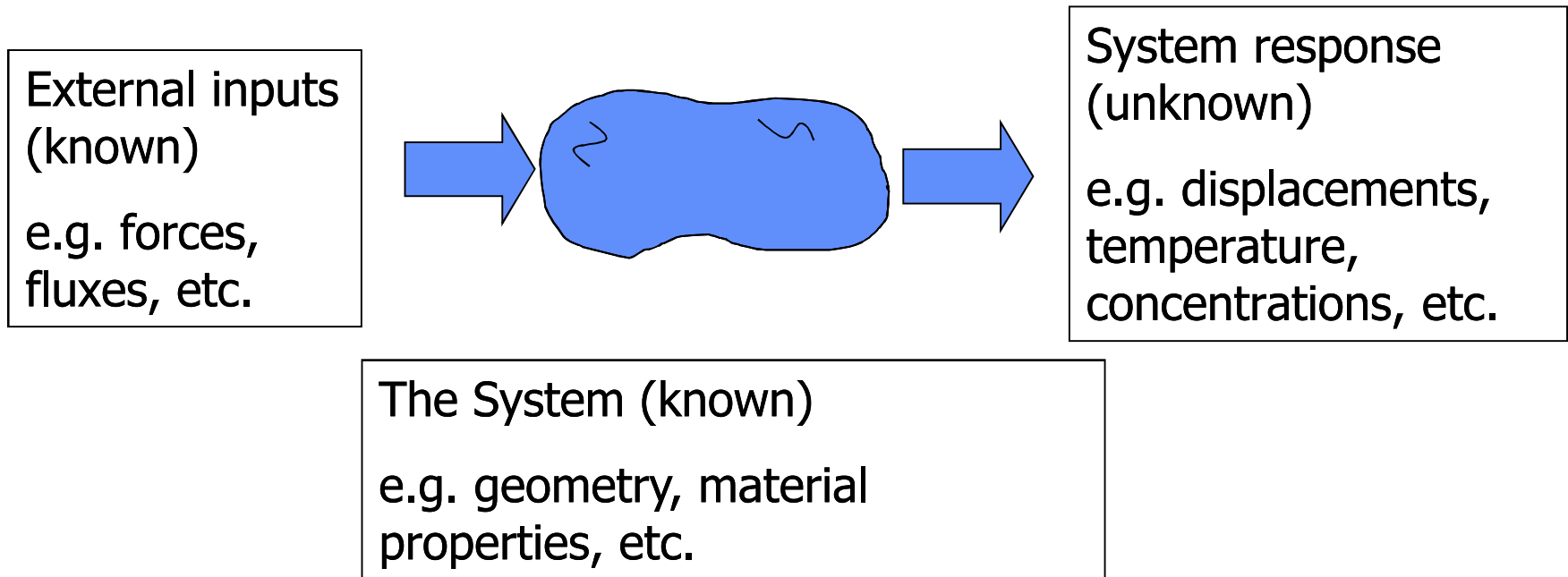


Inverse Problems- Motivation

- **Characterizing energy sources from experimental measurements is a common need in structural acoustics**
 - **acoustic testing of aerospace structures, damage or defect identification from acoustic emission, earthquake modeling, nonproliferation**
- **Determining unknown material properties from measurements is a common need in engineering analysis**
 - **Model calibration, Subsurface modeling, medical ultrasonics**
- **For applications that involve complex geometries and/or sources, finite element modeling is needed for an accurate solution of the forward problem.**
- **Goal: leverage existing massively parallel finite element technology developed for forward problems to solve the inverse problem.**

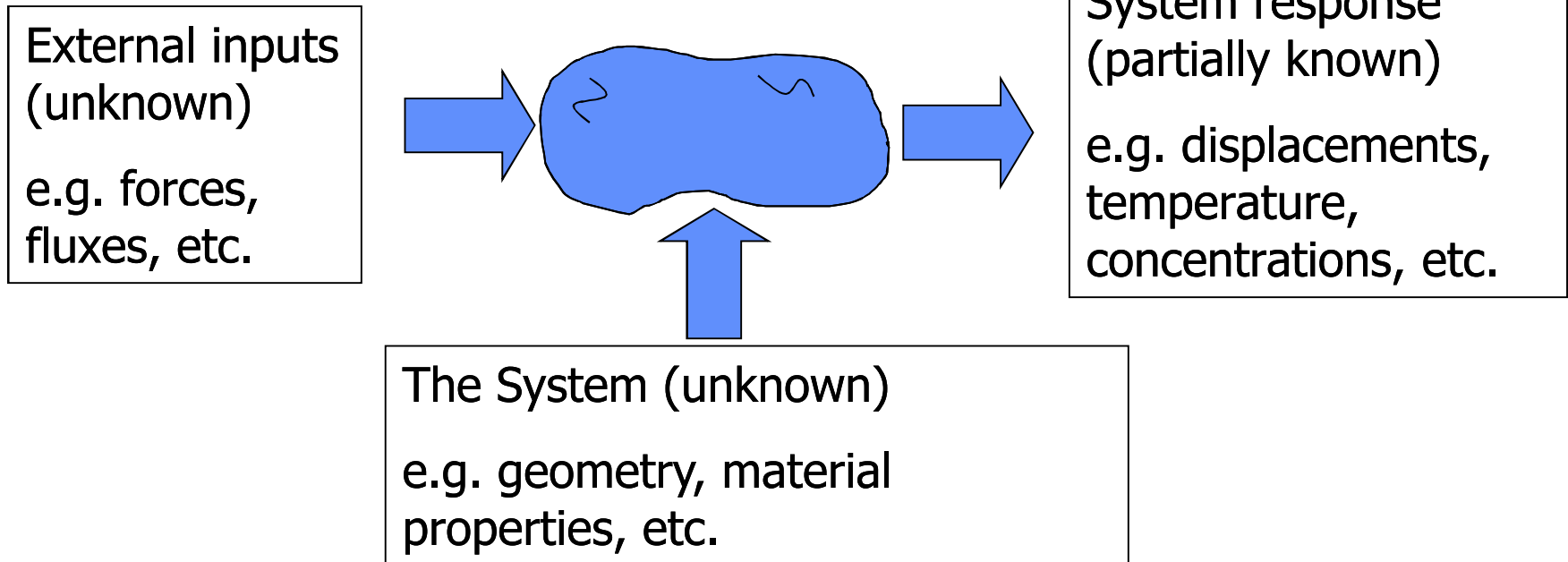
Inverse Problems: The physical View

The direct or forward problem



Inverse Problems: The physical View (2)

One type of inverse problem





Inverse Problems (3) Challenges

- **Usually, inverse problems are ill-posed.**
 - **Solution may not exist.**
 - **Solution may not be unique.**
 - **Solution may be unstable. That is, it may be sensitive to small changes in the input data.**
- **Can be very computationally demanding.**



Inverse Problems of Interest

- **Source inversion for acoustics, structures, and coupled structural acoustics**
 - Determine amplitudes of acoustic sources, given microphone response measurements
 - Determine amplitudes of structural tractions or pressures, given accelerometer measurements
 - Determine both acoustic and structural sources, given both microphone and accelerometer data
- **Material inversion for elastic materials in frequency domain and nonlinear joints in time domain**
 - Determine structural damping parameters to calibrate finite element models
 - Modified Error in Constitutive Equations (MECE)
 - L2 (Least Squares) minimization.



Source Inversion Methodology

- **PDE-constrained optimization approach**
 - Offers flexibility and extensibility
 - Applicable to time-domain, frequency-domain, and nonlinear problems. Can be tailored to each application.
 - Applicable to large numbers of design variables.
 - Allows significant code sharing with material inversion capability (backward time integrators for adjoint problems, experimental data manager, objective function, etc)
- **Massively parallel finite element code Sierra-SD is used for solving the forward and adjoint problems.**
- **Optimization code ROL is used for solving the optimization problem.**

Structural Acoustic Equations of Motion

acoustics

$$\nabla^2 \phi = \frac{1}{c^2} \ddot{\phi}, \quad \text{in } \Omega_f \times (0, T)$$

$$\nabla \phi \cdot \mathbf{n}_f = -\rho_f \ddot{u}_n, \quad \text{on } \partial\Omega_f^N \times [0, T]$$

$$\phi = 0, \quad \text{on } \partial\Omega_f^D \times [0, T]$$

$$\phi(0, T) = 0, \quad \text{in } \Omega_f$$

$$\dot{\phi}(0, T) = 0, \quad \text{in } \Omega_f$$

solid mechanics

$$\nabla \cdot \boldsymbol{\sigma} = \rho \ddot{\mathbf{u}}, \quad \text{in } \Omega \times (0, T)$$

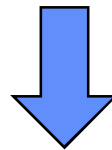
$$\boldsymbol{\sigma} \mathbf{n} = \mathbf{h}, \quad \text{on } \partial\Omega^N \times [0, T]$$

$$\boldsymbol{\sigma} = \mathbf{D} : \nabla \mathbf{u}, \quad \text{in } \Omega \times [0, T]$$

$$\mathbf{u} = \mathbf{0}, \quad \text{on } \partial\Omega^D \times [0, T]$$

$$\mathbf{u}(0, T) = \mathbf{0}, \quad \text{in } \Omega$$

$$\dot{\mathbf{u}}(0, T) = \mathbf{0}, \quad \text{in } \Omega$$



Time domain

$$[M]\mathbf{a}(t) + [C]\mathbf{v}(t) + [K]\mathbf{u}(t) = \mathbf{f}(t)$$

Frequency domain (Helmholtz)

$$[H(\omega)]\mathbf{z}(\omega) = \mathbf{F}(\omega)$$

$$[H(\omega)] = -\omega^2[M] + i\omega[C] + [K]$$



Structural Acoustic Equations of Motion

Fully coupled formulation

$$\begin{bmatrix} M_s & 0 \\ 0 & M_a \end{bmatrix} \begin{bmatrix} \ddot{u} \\ \ddot{\phi} \end{bmatrix} + \begin{bmatrix} C_s & L^T \\ -L & C_a \end{bmatrix} \begin{bmatrix} \dot{u} \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} K_s & 0 \\ 0 & K_a \end{bmatrix} \begin{bmatrix} u \\ \phi \end{bmatrix} = \begin{bmatrix} f_s \\ f_a \end{bmatrix}$$

Condensed notation

$$[M]\mathbf{a}(t) + [C]\mathbf{v}(t) + [K]\mathbf{u}(t) = \mathbf{f}(t)$$

We will use the condensed notation in following slides



Statement of Inverse Problem

Minimize objective function

$$J(\{\mathbf{u}\}, \{\mathbf{p}\}) = \frac{\kappa}{2} \left(\{\mathbf{u}\} - \{\mathbf{u}_m\} \right)^T [\mathbf{Q}] \left(\{\mathbf{u}\} - \{\mathbf{u}_m\} \right) + \mathcal{R}(\{\mathbf{p}\}),$$

$\{\mathbf{u}\}$ State variables (displacement, pressure)

$\{\mathbf{u}_m\}$ Measured data (displacement, pressure)

$\{\mathbf{p}\}$ Unknown parameters (loads, material parameters)

$[\mathbf{Q}]$ Weight matrix

Subject to equations of motion

$$[\mathbf{H}(\omega)] \mathbf{z}(\omega) = \mathbf{F}(\omega)$$

$$[\mathbf{M}] \mathbf{a}(t) + [\mathbf{C}] \mathbf{v}(t) + [\mathbf{K}] \mathbf{u}(t) = \mathbf{f}(t)$$

$$[\mathbf{H}(\omega)] = -\omega^2 [\mathbf{M}] + i\omega [\mathbf{C}] + [\mathbf{K}]$$

Time domain

Frequency domain

Statement of Inverse Problem (2)

The Lagrangian

$$\begin{aligned}\mathcal{L}(\{d\}, \{\hat{d}\}, \{p\}) &= \tilde{J}(\{p\}) + \hat{\mathbf{u}}_0^T \left([M]\mathbf{a}_0 + [C]\mathbf{v}_0 + [K]\mathbf{u}_0 - \mathbf{f}_0(\{p\}) \right) \\ &+ \sum_{k=1}^N \left\{ \hat{\mathbf{u}}_k^T \left([M]\mathbf{a}_k + [C]\mathbf{v}_k + [K]\mathbf{u}_k - \mathbf{f}_k(\{p\}) \right) \right. \\ &\quad + \hat{\mathbf{v}}_k^T [M] \left(\mathbf{v}_k - \mathbf{v}_{k-1} - \Delta t [(1 - \gamma)\mathbf{a}_{k-1} + \gamma\mathbf{a}_k] \right) \\ &\quad \left. + \hat{\mathbf{a}}_k^T [M] \left(\mathbf{u}_k - \mathbf{u}_{k-1} - \Delta t \mathbf{v}_{k-1} - \frac{\Delta t^2}{2} [(1 - 2\beta)\mathbf{a}_{k-1} + 2\beta\mathbf{a}_k] \right) \right\}\end{aligned}$$

where

$$\{d(\{p\})\} = \{ \{u\}, \{v\}, \{a\} \}$$



Optimality conditions

- **Optimality is obtained by setting derivatives of Lagrangian to zero**
- **We will adopt a reduced space approach where we derive reduced gradients from full space approach**
- **Reduced space approach can be derived from full space**

Formulation of Source Inversion Problem – Frequency Domain

$$J(\{u\}_1, \dots, \{u\}_{N_f}) = \frac{\kappa}{2} \sum_{i=1}^{N_f} \left(\overline{\{u\}_i} - \{u_m\}_i \right)^T [Q] \left(\{u\}_i - \{u_m\}_i \right) + \mathcal{R}(\{p\})$$

Objective Function

$$\mathcal{L} = J + \sum_{i=1}^{N_f} \text{Re} \left(\overline{\{w\}_i}^T \left([H(\omega_i)] \{u\}_i - \{F(\{p\})\}_i \right) \right)$$

Lagrangian

KKT conditions:

$$D_{\{w\}_j} \mathcal{L} \cdot \{\delta w\} = 0 \implies [H(\omega_j)] \{u\}_j = \{F(\{p\})\}_j$$

Forward problem

$$D_{\{u\}_j} \mathcal{L} \cdot \{\delta u\} = 0 \implies [H(\omega_j)] \{w\}_j = \kappa [Q] \left(\{u_m\}_j - \{u\}_j \right)$$

Adjoint problem

$$D_{\{p\}} \mathcal{L} \cdot \{\delta p\} = - \sum_{i=1}^{N_f} \text{Re} \left(\left(\overline{\{w\}_j}^T \left[\frac{\partial \{F(\{p\})\}_j}{\partial \{p\}} \right] \right) \{\delta p\} \right) + D_{\{p\}} \mathcal{R}(\{p\}) \cdot \{\delta p\}$$

Gradient

Formulation of Source Inverse Problem – Time Domain

$$J(\{\mathbf{u}\}, \{\mathbf{p}\}) = \frac{\kappa}{2} \left(\{\mathbf{u}\} - \{\mathbf{u}_m\} \right)^T [Q] \left(\{\mathbf{u}\} - \{\mathbf{u}_m\} \right) + \mathcal{R}(\{\mathbf{p}\}), \quad \text{Objective Function}$$

$$\begin{aligned} \mathcal{L}(\{\mathbf{d}\}, \{\hat{\mathbf{d}}\}, \{\mathbf{p}\}) = & \tilde{J}(\{\mathbf{p}\}) + \hat{\mathbf{u}}_0^T \left([M]\mathbf{a}_0 + [C]\mathbf{v}_0 + [K]\mathbf{u}_0 - \mathbf{f}_0(\{\mathbf{p}\}) \right) \\ & + \sum_{k=1}^N \left\{ \hat{\mathbf{u}}_k^T \left([M]\mathbf{a}_k + [C]\mathbf{v}_k + [K]\mathbf{u}_k - \mathbf{f}_k(\{\mathbf{p}\}) \right) \right. \\ & \quad + \hat{\mathbf{v}}_k^T [M] \left(\mathbf{v}_k - \mathbf{v}_{k-1} - \Delta t [(1-\gamma)\mathbf{a}_{k-1} + \gamma\mathbf{a}_k] \right) \\ & \quad \left. + \hat{\mathbf{a}}_k^T [M] \left(\mathbf{u}_k - \mathbf{u}_{k-1} - \Delta t \mathbf{v}_{k-1} - \frac{\Delta t^2}{2} [(1-2\beta)\mathbf{a}_{k-1} + 2\beta\mathbf{a}_k] \right) \right\} \end{aligned} \quad \text{Lagrangian}$$

$$\nabla_{\{\mathbf{p}\}} \tilde{J} = \nabla_{\{\mathbf{p}\}} \mathcal{L} = - \sum_{k=1}^N \hat{\mathbf{u}}_k^T \left(\nabla_{\{\mathbf{p}\}} \mathbf{f}_k(\{\mathbf{p}\}) \right) + \nabla_{\{\mathbf{p}\}} \mathcal{R}. \quad \text{Gradient Equation}$$

Statement of Inverse Problem (3)

Gateaux derivatives of the Lagrangian with respect to adjoint variables

$$\nabla_{\mathbf{a}_0} \mathcal{L} \cdot \delta \mathbf{a}_0 = \delta \mathbf{a}_0^T \left([M] \hat{\mathbf{u}}_0 - \frac{\Delta t^2}{2} (1 - 2\beta) [M] \hat{\mathbf{a}}_1 - \Delta t (1 - \gamma) [M] \hat{\mathbf{v}}_1 \right),$$

$$\nabla_{\mathbf{u}_k} \mathcal{L} \cdot \delta \mathbf{u}_k = \delta \mathbf{u}_k^T \left([M] (\hat{\mathbf{a}}_k - \hat{\mathbf{a}}_{k+1}) + [K] \hat{\mathbf{u}}_k + \kappa [Q] (\mathbf{u}_k - \mathbf{u}_{m_k}), \right),$$

$$\nabla_{\mathbf{v}_k} \mathcal{L} \cdot \delta \mathbf{v}_k = \delta \mathbf{v}_k^T \left([C] \hat{\mathbf{u}}_k - \Delta t [M] \hat{\mathbf{a}}_{k+1} + [M] \hat{\mathbf{v}}_k - [M] \hat{\mathbf{v}}_{k+1} \right),$$

$$\begin{aligned} \nabla_{\mathbf{a}_k} \mathcal{L} \cdot \delta \mathbf{a}_k &= \delta \mathbf{a}_k^T \left([M] \hat{\mathbf{u}}_k - \beta \Delta t^2 [M] \hat{\mathbf{a}}_k - \frac{\Delta t^2}{2} [M] (1 - 2\beta) \hat{\mathbf{a}}_{k+1}, \right. \\ &\quad \left. - \Delta t [M] (\gamma \hat{\mathbf{v}}_k + (1 - \gamma) \hat{\mathbf{v}}_{k+1}) \right), \end{aligned}$$

$$\nabla_{\mathbf{u}_N} \mathcal{L} \cdot \delta \mathbf{u}_N = \delta \mathbf{u}_N^T \left([M] \hat{\mathbf{a}}_N + [K] \hat{\mathbf{u}}_N + \kappa [Q] (\mathbf{u}_N - \mathbf{u}_{m_N}) \right),$$

$$\nabla_{\mathbf{v}_N} \mathcal{L} \cdot \delta \mathbf{v}_N = \delta \mathbf{v}_N^T \left([C] \hat{\mathbf{u}}_N + [M] \hat{\mathbf{v}}_N \right),$$

$$\nabla_{\mathbf{a}_N} \mathcal{L} \cdot \delta \mathbf{a}_N = \delta \mathbf{a}_N^T \left([M] \hat{\mathbf{u}}_N - \Delta t^2 \beta [M] \hat{\mathbf{a}}_N - \Delta t \gamma [M] \hat{\mathbf{v}}_N \right).$$

Statement of Inverse Problem (4)

(i) Final conditions

$$\begin{aligned}[C]\hat{\mathbf{u}}_N + [M]\hat{\mathbf{v}}_N &= \mathbf{0} \\ \hat{\mathbf{u}}_N &= \Delta t^2 \beta \hat{\mathbf{a}}_N + \Delta t \gamma \hat{\mathbf{v}}_N \\ [M]\hat{\mathbf{a}}_N + [K]\hat{\mathbf{u}}_N &= \kappa[Q](\mathbf{u}_{m_N} - \mathbf{u}_N)\end{aligned}$$

(ii) Backward transition equations

$$\begin{aligned}\hat{\mathbf{u}}_k - \beta \Delta t^2 \hat{\mathbf{a}}_k - \Delta t \gamma \hat{\mathbf{v}}_k &= \frac{\Delta t^2}{2} (1 - 2\beta) \hat{\mathbf{a}}_{k+1} + \Delta t (1 - \gamma) \hat{\mathbf{v}}_{k+1} \\ [C]\hat{\mathbf{u}}_k + [M](\hat{\mathbf{v}}_k - \Delta t \hat{\mathbf{a}}_{k+1} - \hat{\mathbf{v}}_{k+1}) &= \mathbf{0} \\ [M]\hat{\mathbf{a}}_k + [K]\hat{\mathbf{u}}_k &= [M]\hat{\mathbf{a}}_{k+1} + \kappa[Q](\mathbf{u}_{m_k} - \mathbf{u}_k)\end{aligned}$$

(iii) Last transition equation

$$\hat{\mathbf{u}}_0 = \frac{\Delta t^2}{2} (1 - 2\beta) \hat{\mathbf{a}}_1 + \Delta t (1 - \gamma) \hat{\mathbf{v}}_1$$

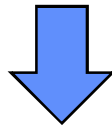


Statement of Inverse Problem (5)

Gateaux derivatives of the Lagrangian with respect to design variables

$$\nabla_{\{p\}} \mathcal{L}(\{d\}, \{\hat{d}\}, \{p\}) \cdot \{\delta p\} = \nabla_{\{d\}} \mathcal{L} \cdot \{\delta d\} + \nabla_{\{p\}} \mathcal{L} \cdot \{\delta p\}$$

$$\nabla_{\{d\}} \mathcal{L} = 0 \quad (\text{from adjoint solution})$$



Gradient Equation

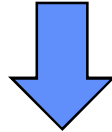
$$\nabla_{\{p\}} \tilde{J} = \nabla_{\{p\}} \mathcal{L} = - \sum_{k=1}^N \hat{u}_k^T \left(\nabla_{\{p\}} \mathbf{f}_k(\{p\}) \right) + \nabla_{\{p\}} \mathcal{R}.$$



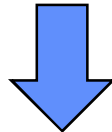
Solution of Inverse Problem

Do until tolerance $<$ eps

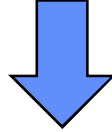
Solve forward problem



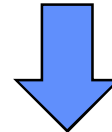
Solve adjoint problem



Compute gradients, Hessians



Optimization step



Receive design variable updates from optimization solver

end



Sierra-SD: A Brief History

- **Sierra-SD was created in the 1990's at Sandia National Laboratories for large-scale structural analysis**
- **Intended for extremely complex structural and structural acoustics models**
 - **Commonly used to solve models with 100's of millions of degrees of freedom**
- **Scalability is the key**
 - **Sierra-SD can solve n-times larger problem using n-times many more compute processors, in nearly constant CPU time**



Rapid Optimization Library (ROL)

- **Challenge:** Optimization software typically lacks support for large-scale computing.
 - optimization variables cannot be distributed across processors
 - ➡ limited to very small inverse and optimal design problems
 - no support for iterative linear system solvers
 - ➡ slow (or no) convergence due to solver inexactness
- **Requirements:**
 - **Matrix-free:** The application developer, *not the optimization software*, defines how matrices and vectors are stored/used, and chooses the linear system solver.
 - **Robust:** The optimization software manages the linear solver accuracy.
 - **ROL/PEOpt is based on vector-space abstractions, through polymorphism mechanisms of C++.**
 - **User defines: copy, axpy, scal, zero, innr; and objective function evaluation, gradient, Hessian.**
 - **ROL/PEOpt supports a variety of algorithms: nonlinear CG, Gauss-Newton, full-space SQP, etc., all with trust regions and line search.**

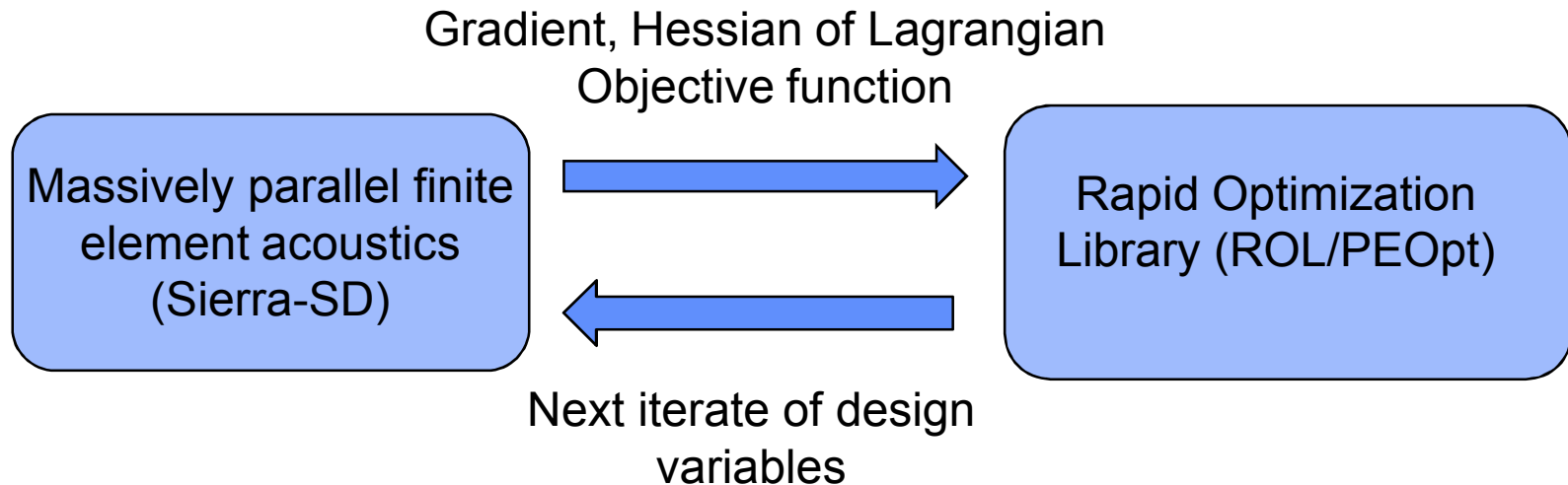
[Available in Trilinos in 2013!](#)

Denis Ridzal, Joseph Young (Sandia)



Interaction of Finite Element and Optimization Codes

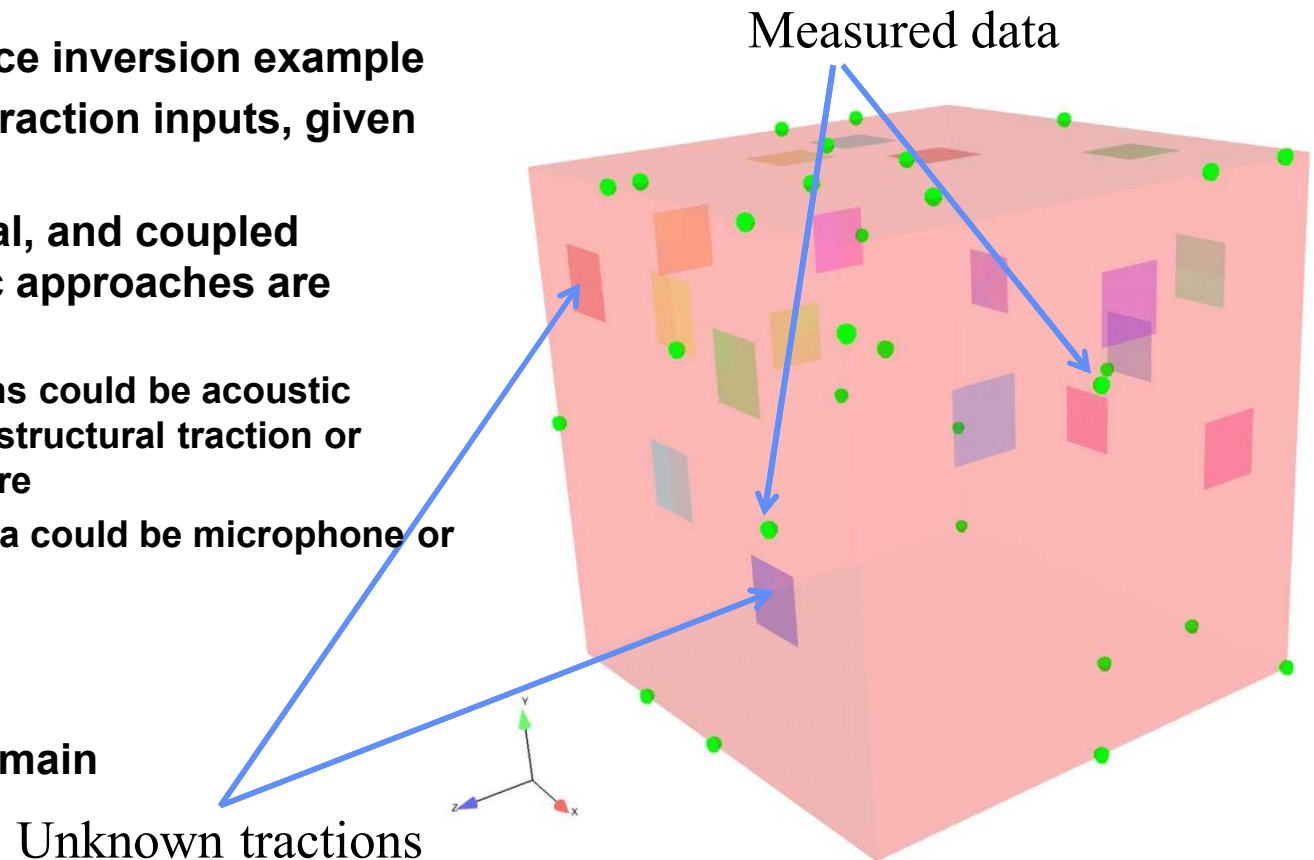
Finite Element and Optimization Codes operate as independent entities



- The adjoint method is used to compute the gradients and Hessians

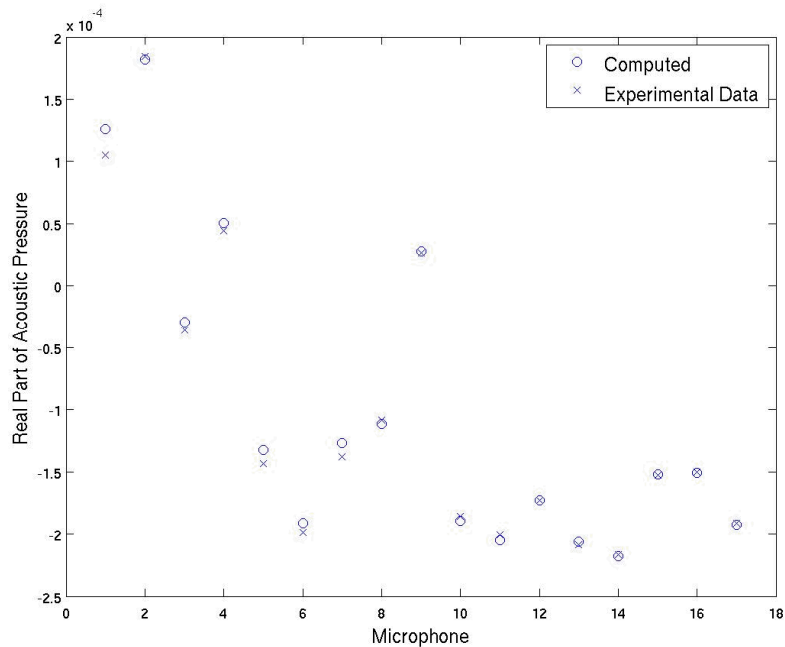
3D Source Inversion Test

- Schematic of source inversion example
- Goal is to predict traction inputs, given measurement data
- Acoustic, structural, and coupled structural acoustic approaches are identical
 - Unknown tractions could be acoustic particle velocity, structural traction or structural pressure
 - Measurement data could be microphone or accelerometer
- Two approaches:
 1. Time domain
 2. Frequency domain

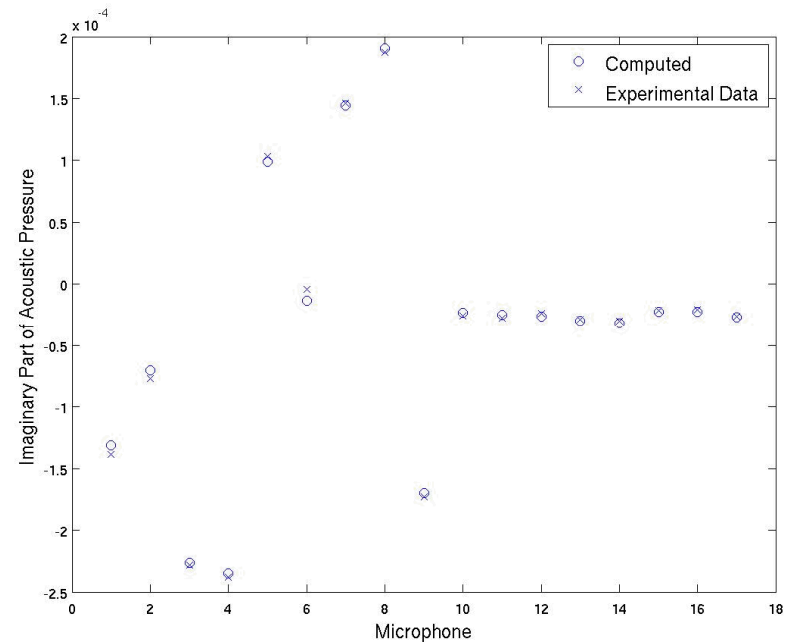


Frequency Domain Source Inversion

Single Frequency Results



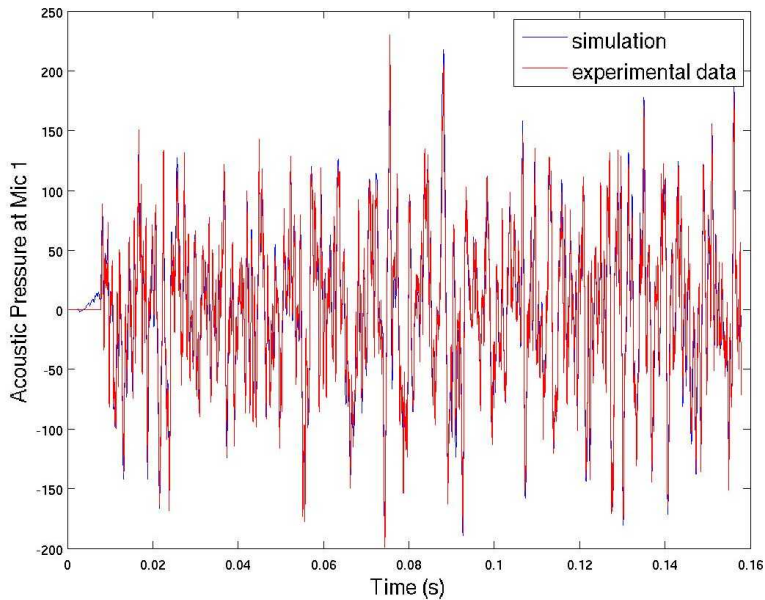
Real part of acoustic pressure



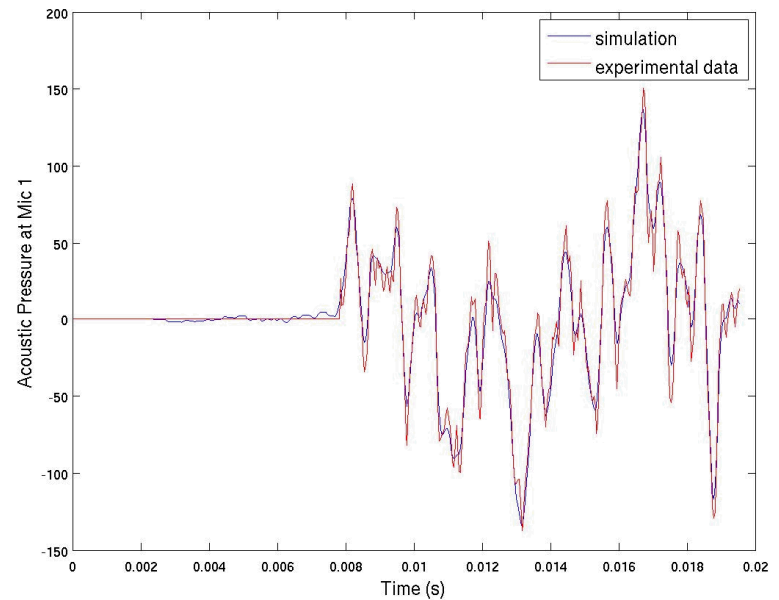
Imaginary part of acoustic pressure

Time Domain Source Inversion

Results for Microphone 1 (other mics were similar)



Full time history



Blow-up near origin of wave



Conclusions

- **Massively parallel finite element structural acoustics and optimization codes have been loosely coupled for the solution of source and material inversion problems.**
- **Adjoint methods have been implemented in Sierra-SD in both time and frequency domains.**
- **Applicable to large-scale models with many degrees of freedom.**
- **The method allows flexibility to work with both time and frequency domain, and nonlinear problems.**
- **Method has been applied to solving both source and material inversion on problems of interest.**