Development of a Hyperspectral Tomography Sensor for Practical Propulsion Devices

Lin Ma

Assistant Professor
Department of Mechanical Engineering
Clemson University, Clemson, SC 29634
LinMa@clemson.edu

Goal: Develop new tomographic techniques to
- reduce number of projections
- map multiple quantities simultaneously

Approach: Use hyperspctral information content

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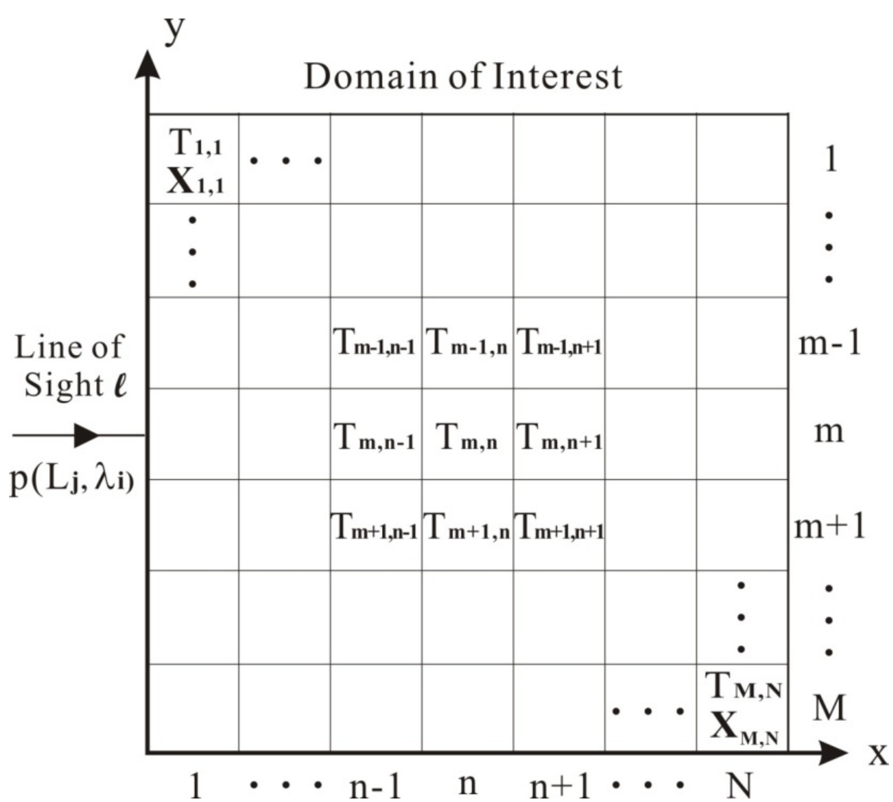
Background – Tomography

- Tomography: Imaging by line-of-sight-averaged projections
- A mature technique in many areas (medicine, archeology, etc)



Background – Limitations

Limitations of traditional tomographic technique

- Too many projections
  e.g. 10x10 grid→100 unknowns→100+ equations→100+ projections
- Impractical in many areas where temporal resolution/cost is a concern
  Engine monitoring, combustion control, etc

Our approach – Add wavelengths to reduce the number of projections (hyperspectral absorption spectroscopy)

The 10x10 example again: if each projection contains 5 wavelengths
→ 100 equations to solve for 100 unknowns
→ 20 projections
→ A fivefold reduction of projections compared with single-λ technique

Facilitated by wavelength-multiplexing technologies and new broadband laser sources

Background
Tomographic Inversion Algorithm

Existing algorithms cannot be directly applied to:

- Incorporate multiple wavelengths, i.e. effectively exploited the multispectral information content
- Address the highly nonlinear nature of absorption spectroscopy

$$S(T,\lambda_i) = S(T_0,\lambda_i)\cdot\frac{Q(T)}{Q(T_0)}\cdot\exp[-\frac{hcE''}{k}\cdot(\frac{1}{T}-\frac{1}{T_0})]\cdot\frac{1-\exp(-\frac{hc^2}{kT\lambda_i})}{1-\exp(-\frac{hc^2}{kT_0\lambda_i})}$$

Our approach:

- Formulate the problem into a minimization problem
- Solve the minimization problem by a robust global algorithm
- Flexibly utilize *a priori* information to regulate the minimization problem

Summary
Hyperspectral Absorption Tomography

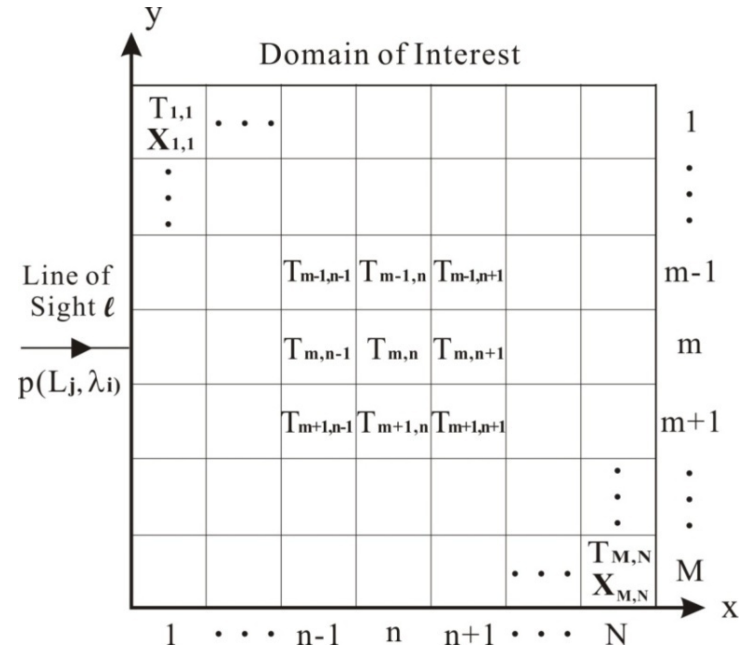
- Absorption Spectroscopy

$$p(L_j,\lambda_i) = P\int_a^b S[T(x,y),\lambda_i]\cdot X(x,y)\cdot dl$$

T(x,y) and X(x,y) are the temperature and concentration distributions to be imaged

L_j the jth projection location

λ_i the ith wavelength



- The minimization formulation

$$D(T,X) = \sum_{j=1}^{J}\sum_{i=1}^{I}[p_m(L_j,\lambda_i) - p_c(L_j,\lambda_i)]^2$$

D reaches its minimal (zero) when T and X matches the true distribution.

- The incorporation of regularization (*a priori* constraints)

$$F(T,X) = D(T,X) + \gamma_T\cdot R_T(T) + \gamma_X\cdot R_X(X)$$

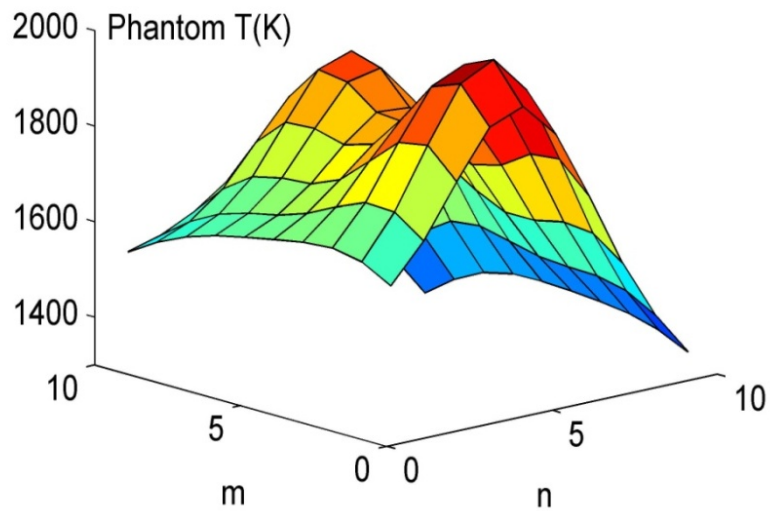
Sample Phantoms

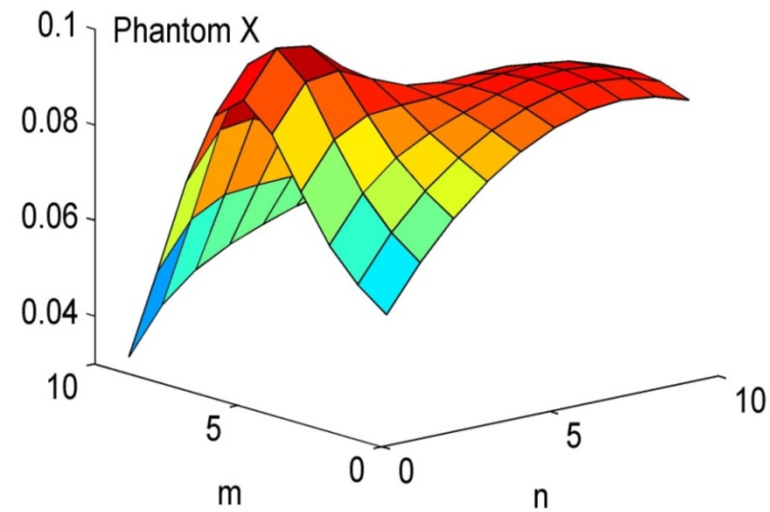
Simulation conditions:

10x10 grid
10 wavelengths
20 projections

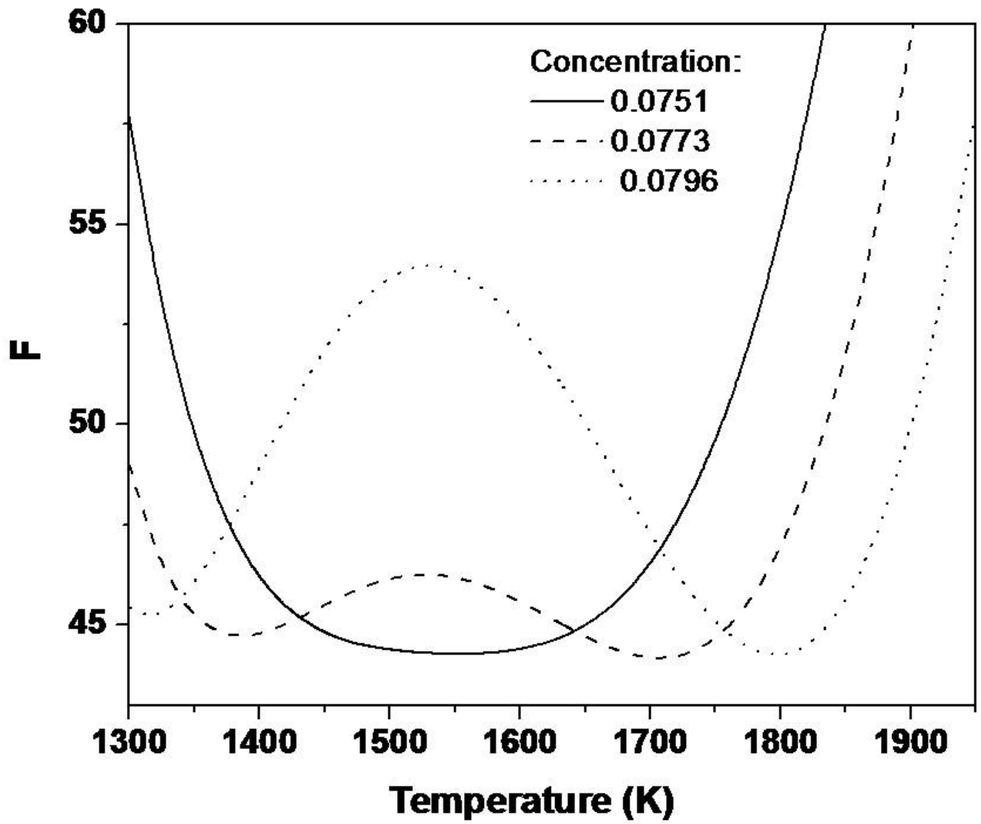
Phantoms created to simulate the multimodal T and X distributions in practice

The T and X phantoms





A Difficult Minimization Problem



F is a complicated function (multiple local minima with similar amplitudes) and is difficult to minimize.

An advanced minimization algorithm (simulated annealing) overcomes this difficulty.

Background
Simulated Annealing and Regularization

- **Simulated Annealing (SA)**
  1. A statistical minimization method
  2. Simulates how solids anneal
  3. A non-greedy method and a global method
- **Regularization**

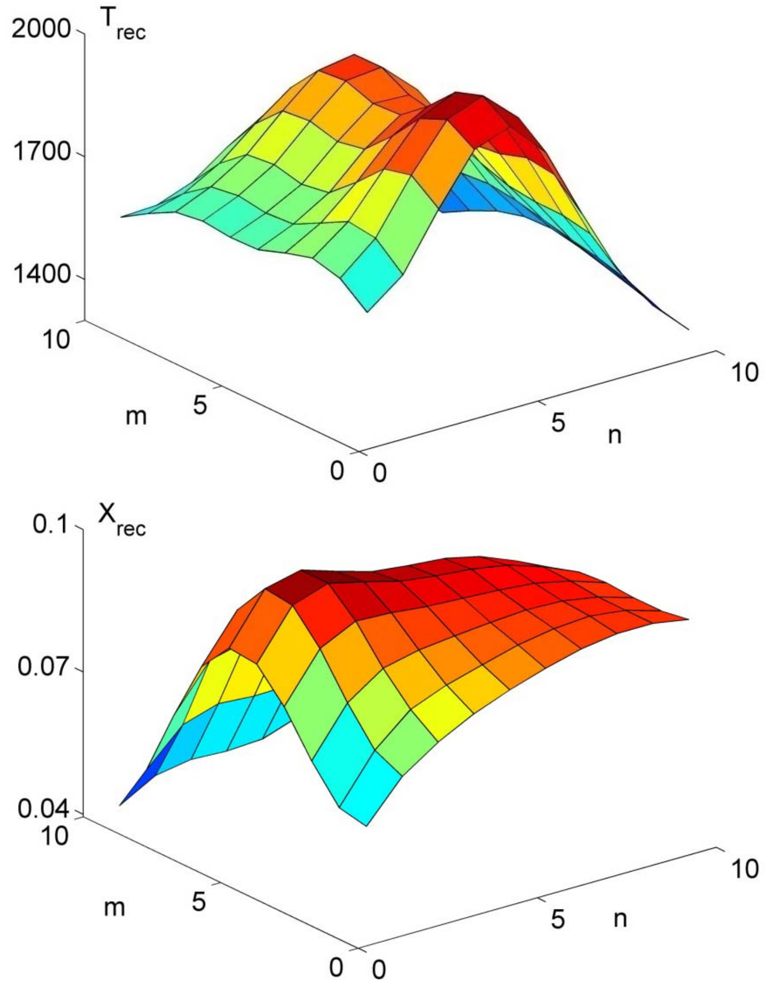
$$F(T,X) = D(T,X) + \gamma_T \cdot R_T(T) + \gamma_X \cdot R_X(X)$$

1. R_T and R_X contains the *a priori* information, i.e., smoothness, bounds, boundary conditions, etc.
2. Determination of optimal γ_T and γ_C not trivial in nonlinear problems
3. Details see our papers

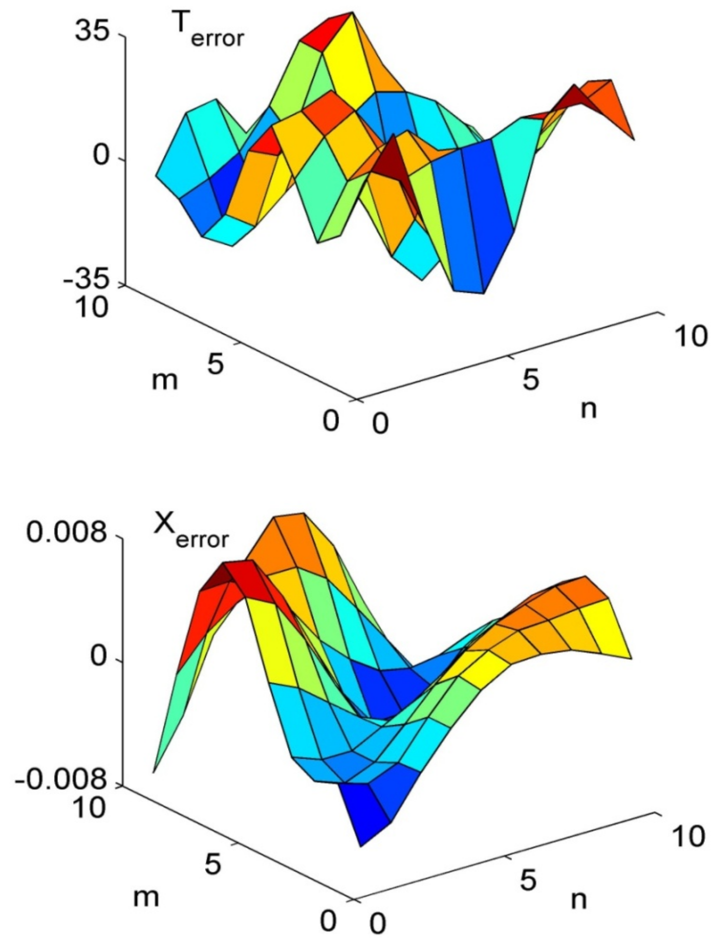
Numerical investigation of hyperspectral tomography for simultaneous temperature and concentration imaging, Applied Optics, v47, Issue 21, pp.3751, 2008.
Determine the optimal regularization parameters in hyperspectral tomography, Applied Optics, in press.

Sample Reconstruction Results

The reconstructed T and X distributions

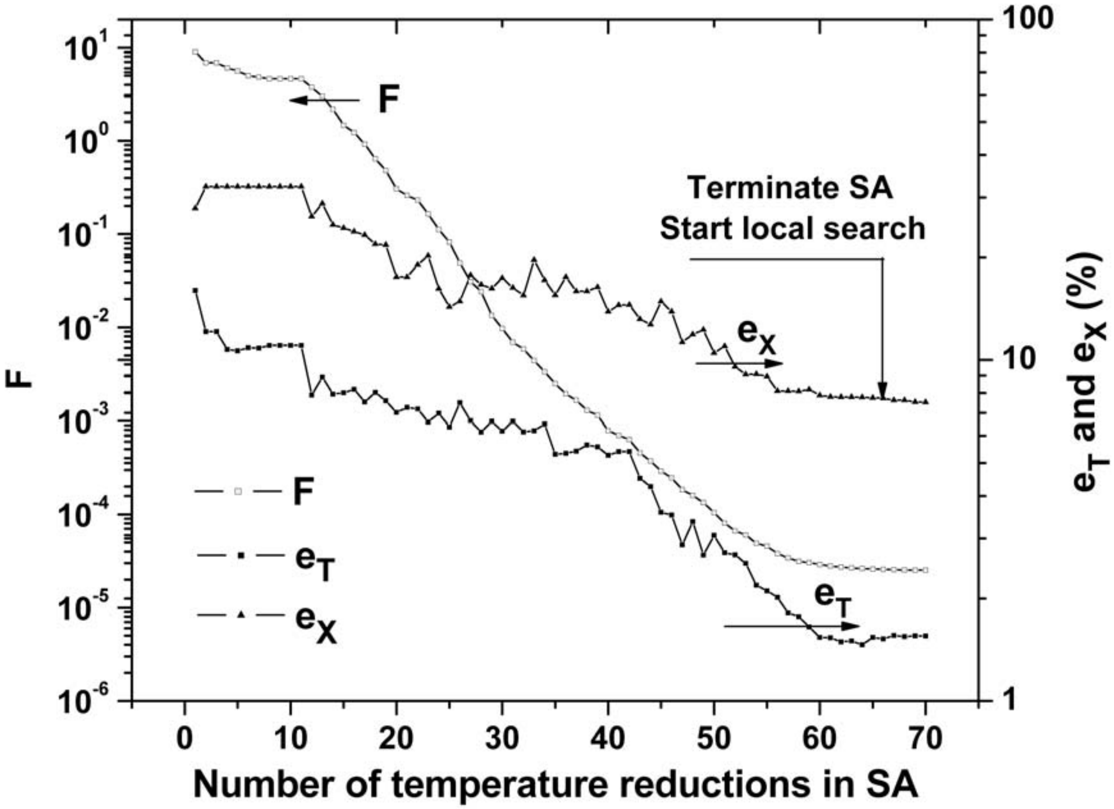


The reconstruction errors



- Excellent imaging fidelity with significantly fewer projections

A Typical Minimization Process



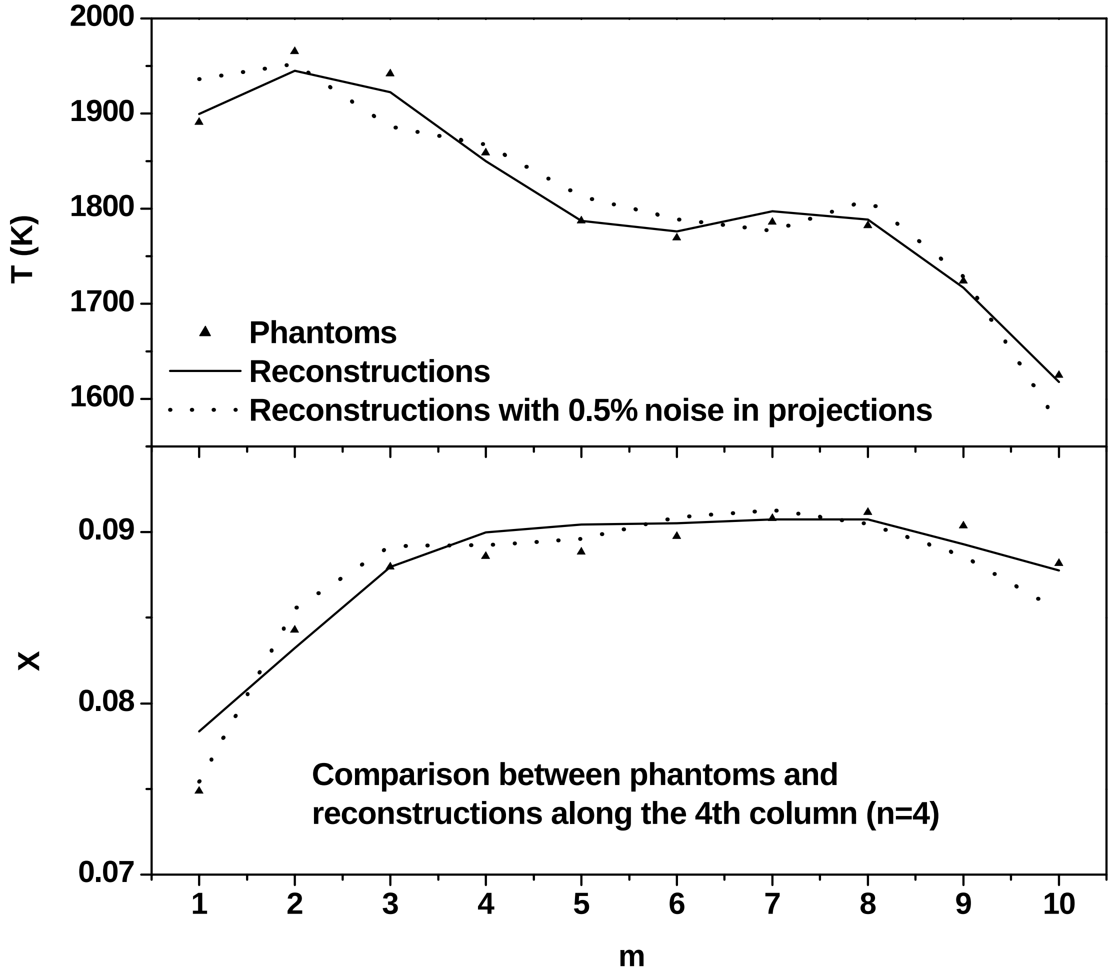
$$e_T = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} | T_{m,n}^{rec} - T_{m,n} |}{\sum_{m=1}^{M}\sum_{n=1}^{N} | T_{m,n} |}$$

$$e_X = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} | X_{m,n}^{rec} - X_{m,n} |}{\sum_{m=1}^{M}\sum_{n=1}^{N} | X_{m,n} |}$$

$\gamma_T = 1\times10^{-10}$ and $\gamma_x = 1\times10^{-2}$

- e_T and e_x characterize the overall reconstruction quality
- The Simulated Annealing technique provides robust and effective solution to the problem

A Closer Look at the Reconstruction



- The reconstruction quality remains good with error in the projections

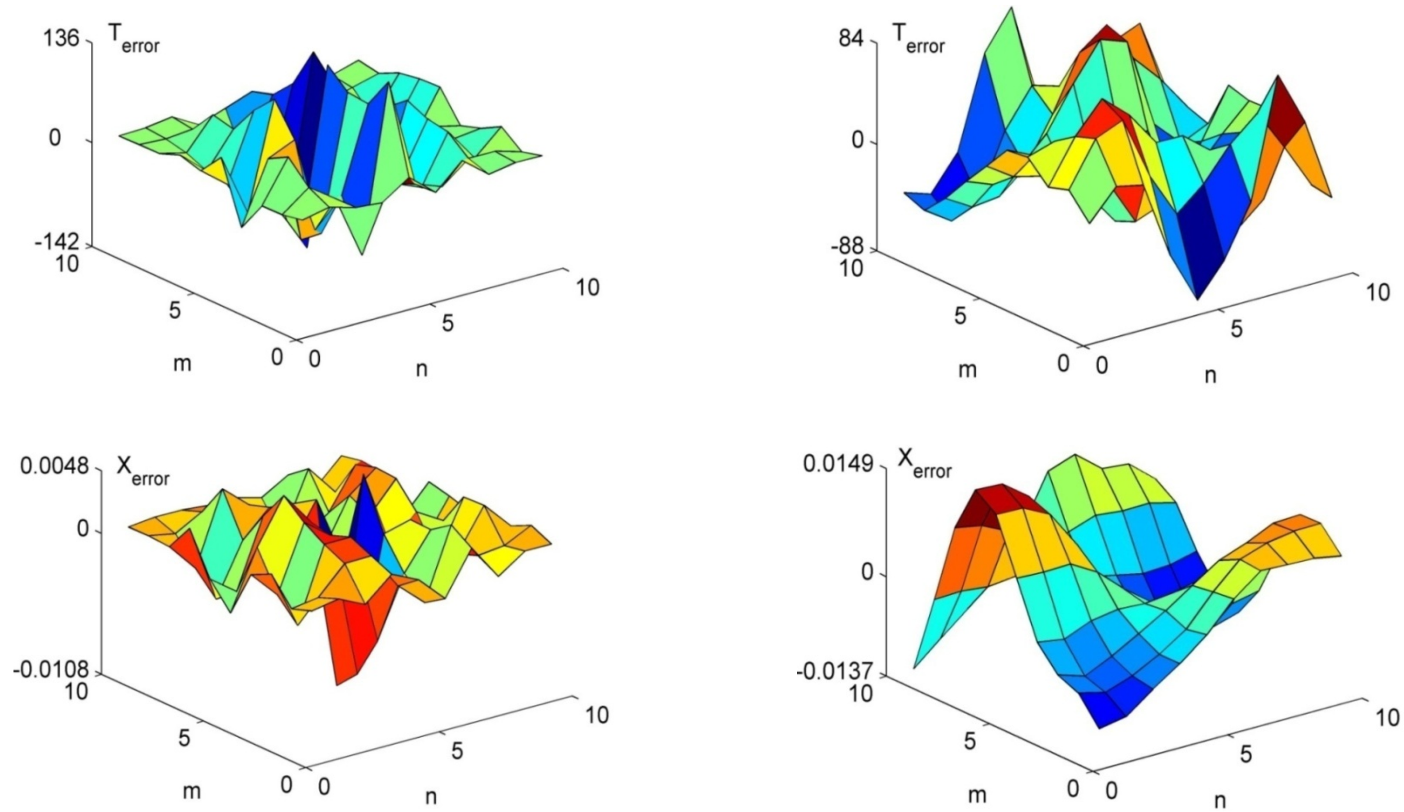
Hyperspectral Tomography Enhances Reconstruction Stability

Simulation Conditions

10x10 grid
0.5% random noise in projections

2-Wavelength
100 projections

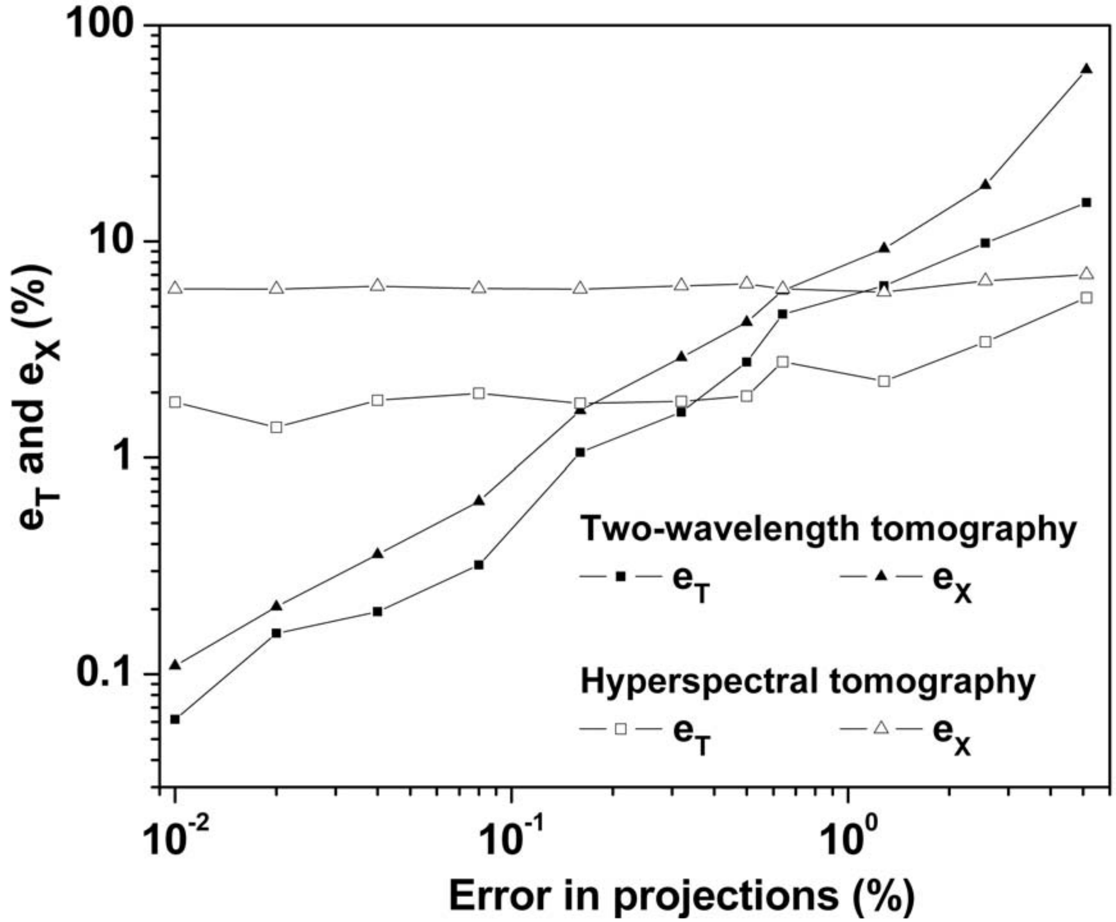
Hyperspectral
20 projections, 10 wavelengths



• 2-wavelength unable to maintain good sensitivity when temperature non-uniformity is prominent → reconstruction sensitive to noise

• Hyperspectral information content ameliorates this problem

Technique Insensitive to Measurement Noise



- Technique stable in the presence of measurement error.
- Superior stability over single- or two-wavelength tomography techniques
- Ongoing investigation to improve X measurements

Conclusions

A tomographic imaging technique has been developed to

- **Exploit the hyperspectral information content enabled by broadband lasers**
- **Provide simultaneous imaging of temperature and chemical species concentration**
- **Reduce the number of projections significantly**
- **Enhance the reconstruction stability against measurement uncertainty**

Experimental demonstration underway.