A HYBRID PRIOR MODEL FOR TUNABLE DIODE LASER ABSORPTION TOMOGRAPHY

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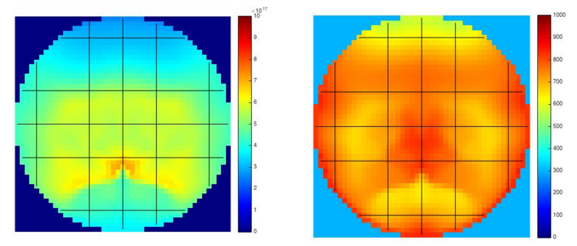
Background

- **Tunable diode laser absorption tomography (TDLAT):** An application to measure concentration *(N)* and temperature *(T)* of gaseous media using light absorbance
- **Challenges of TDLAT**: Very few measurements (~40), large no. of unknowns (~3194)



Concentration (molecules/cm³) Temperature (kelvins)

- **Conventional Methods:** Simplifying assumptions → Suboptimal results

Model Based Iterative Reconstruction (MBIR) Methods

- **MBIR Methods:** Use a statistical model for measurement process as well as unknown concentration and temperature

$$\hat{x} = \underset{x}{\operatorname{argmax}}(\log p(y|x) + \log p(x))$$

- x - unknown vector; y - measurement vector
- $p(y|x)$ - Forward Model; $p(x)$ - Prior Model

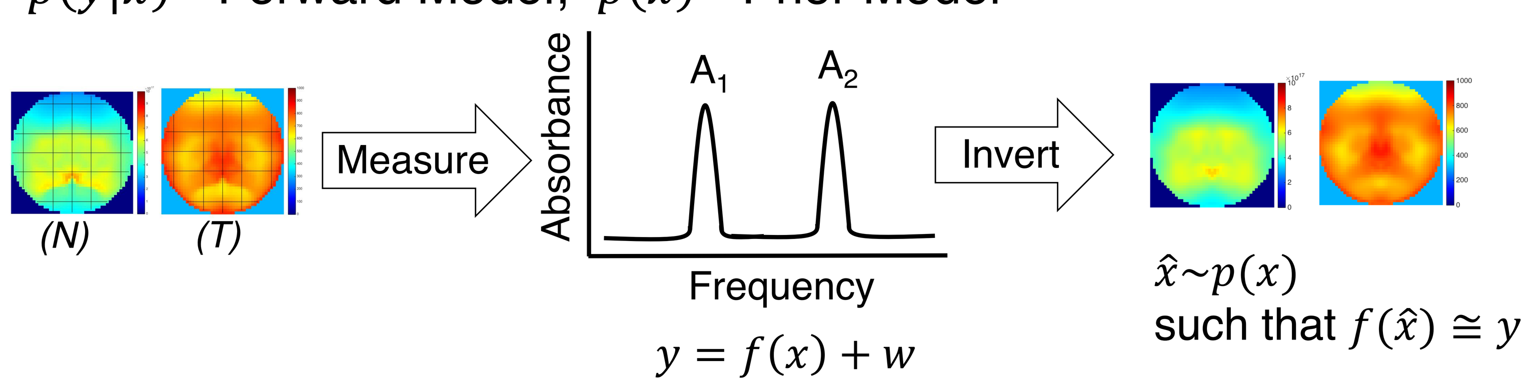
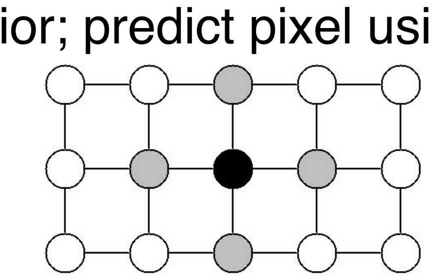


Illustration of model based inversion for tunable diode laser absorption tomography

Hybrid Gaussian Prior Model

- Prior models incorporates existing knowledge in reconstruction process
- **Examples**: Markov Random Field (MRF), Gaussian distribution
- **MRF:** A smoothing prior; predict pixel using neighbors

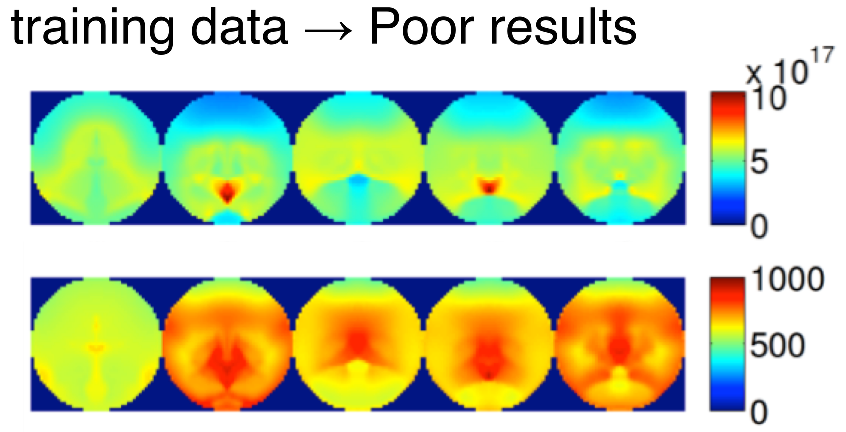


MRF uses a graph structure

- **Conventional Gaussian distribution:** Estimate mean and covariance
  - Requires training data
  - Good training data → Good results
  - Poor training data → Poor results

Concentration

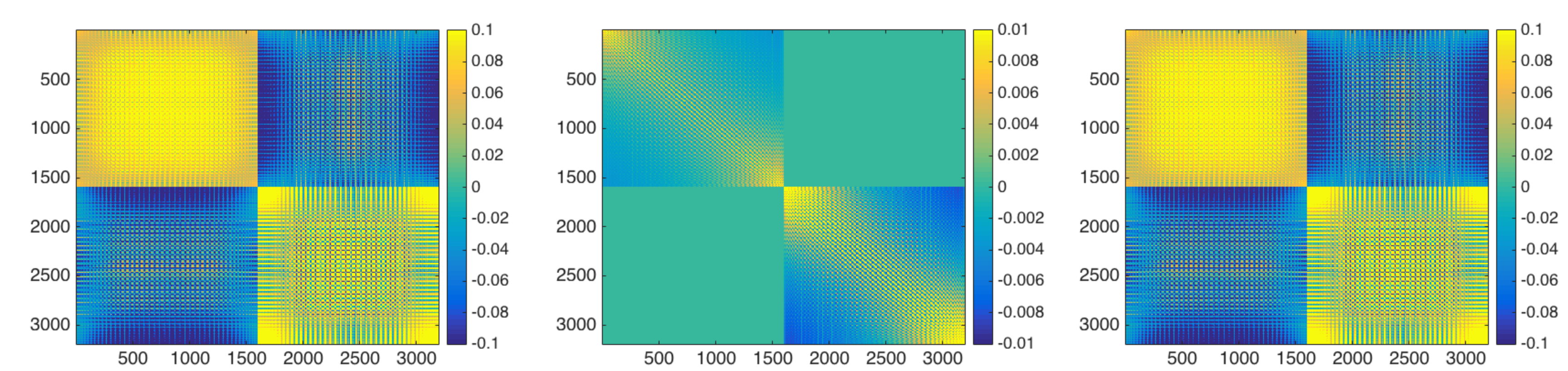
Temperature



- **Challenges:**
  - MRF → Very simplistic, doesn't give good results always
  - Conventional Gaussian → Results depend on the accuracy of the training data
- **Proposed Solution:** Use a hybrid between Gaussian MRF and a conventional Gaussian prior

$$p(x) = \frac{|R|^{-\frac{1}{2}}}{(2\pi)^{n/2}} \exp\left(-\frac{1}{2}(x-\mu)^t R^{-1}(x-\mu)\right)$$

- μ – DC Valued mean
- $R = \gamma\, R_{sample} + (1-\gamma)\, R_{MRF}$

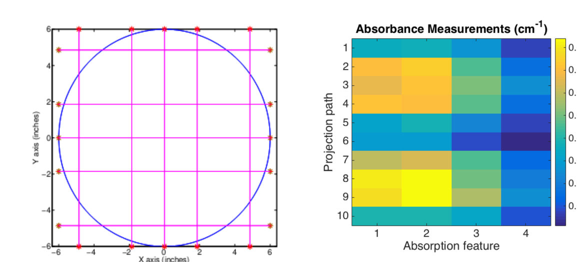


Forward Model

- Total 10 projection paths, 4 absorption features

$$y = Hf(x) + w$$

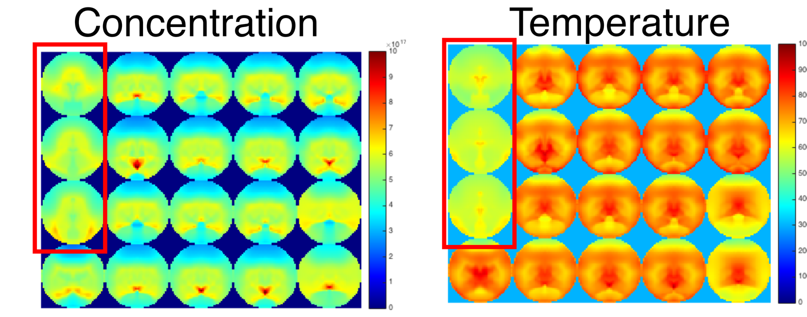
- $y \in \mathbb{R}^{40}, x \in \mathbb{R}^{3194}$
- f is a non-linear function; models physics
- w additive white Gaussian noise
- SNR: 30dB



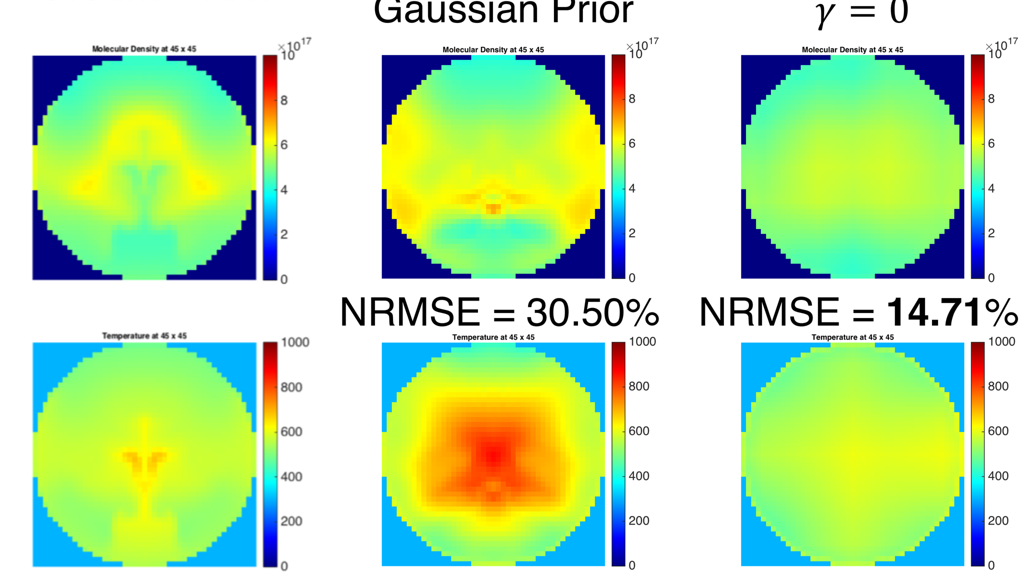
Measurement Schematic Example Measurement Data

Results

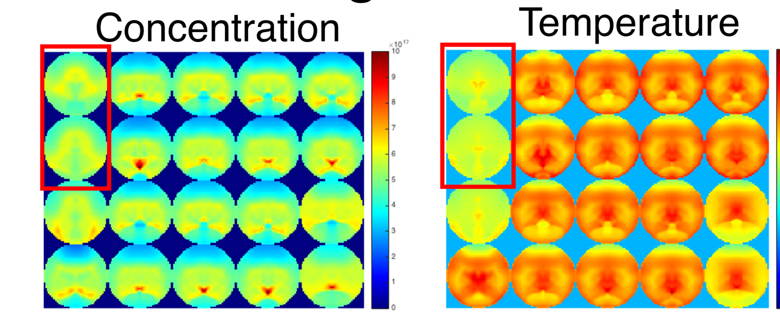
Non-representative Training Data



Training data; boxed phantoms are test cases



Moderately Representative Training Data



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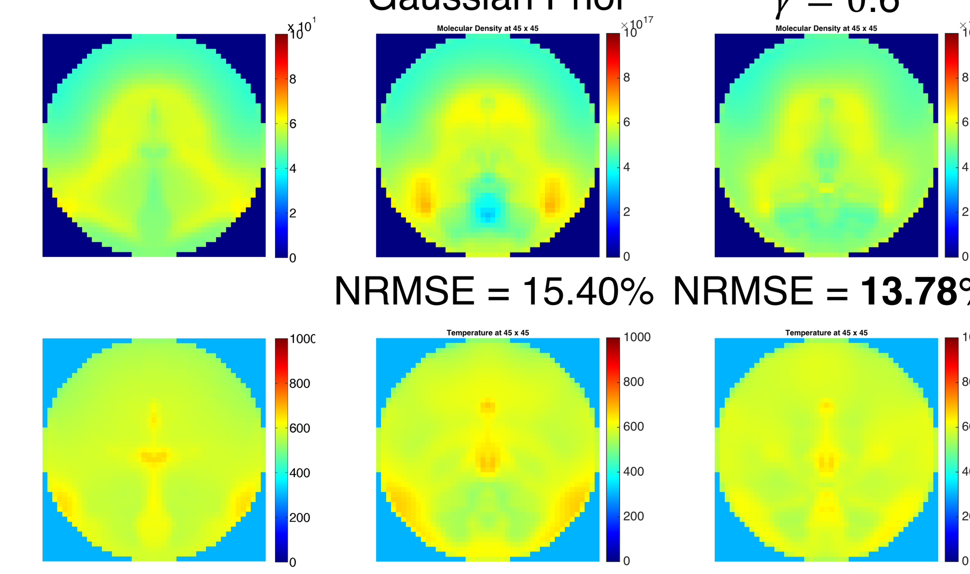
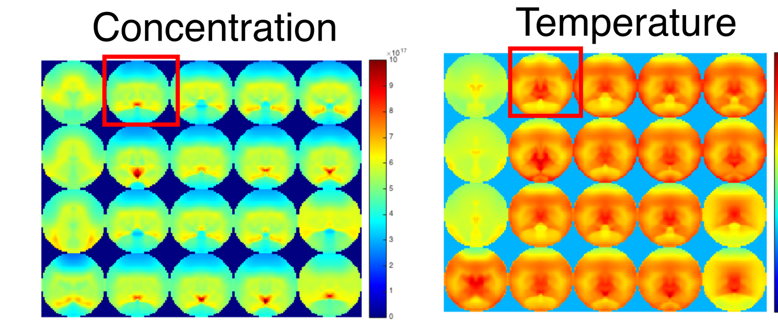
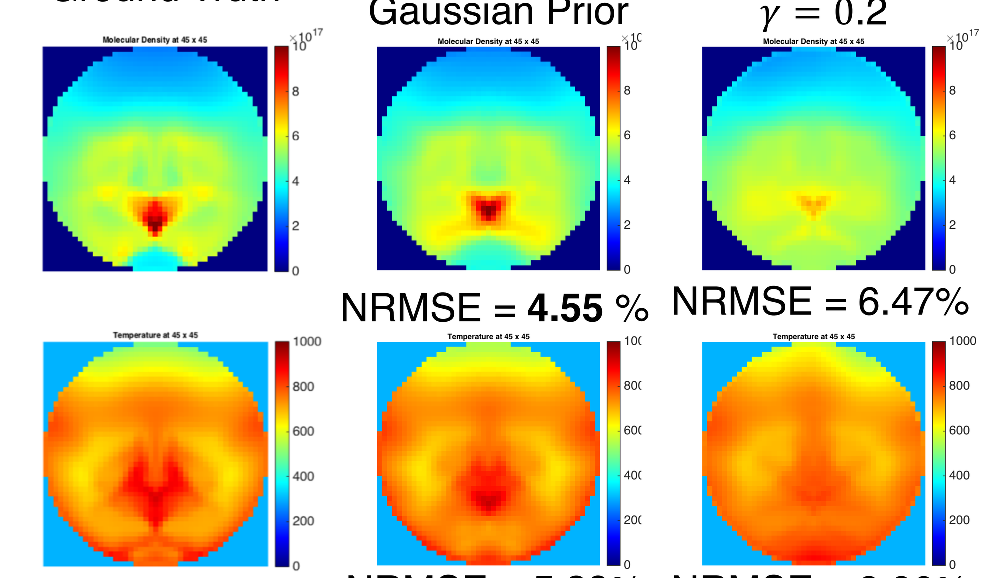


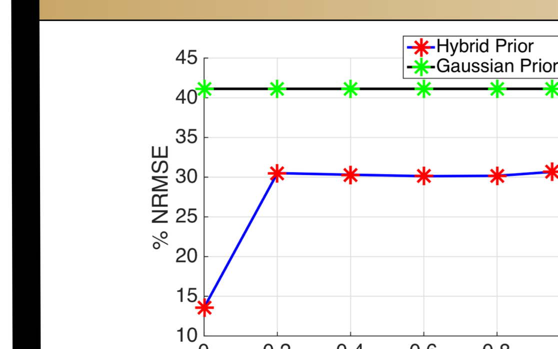
Sufficiently Representative Training Data



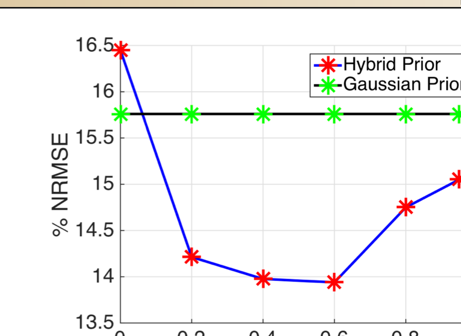
Training data; boxed phantoms are test cases



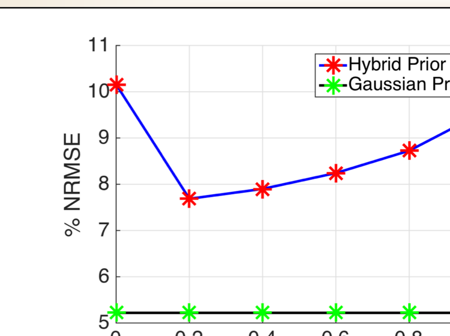
Summary



Non-representative training data



Moderately non-representative training data



Sufficiently representative training data

- Presented a Hybrid Gaussian prior model for images
- Hybrid prior can be tuned according to accuracy of training data
- Easy to train, flexible prior model
- Better reconstruction results