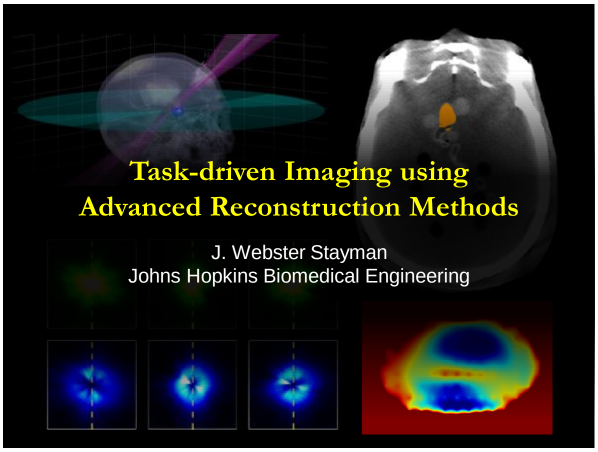
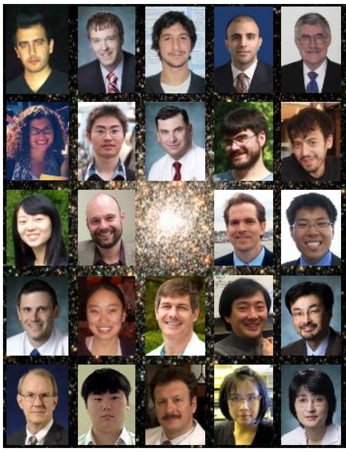


Task-driven Imaging using Advanced Reconstruction Methods

J. Webster Stayman
Johns Hopkins Biomedical Engineering



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Advanced Reconstruction Methods

Tend to be implicitly defined optimizers of an objective function

$$\hat{\mu} = \arg\min \Phi(\mu; y)$$

e.g., $\Phi(\mu; y) = \|F(\mu) - y\|$

$\Phi(\mu; y) = \|\mathbf{A}\mu - F(y)\|$

- Enforce similarity between modeled projections of an object estimate and the data
- Typically solved through iterative approximation

Relatively easy to generalize and include additional information

- Various noise models – likelihood functions $\Phi(\mu; y) = -L(\mu; y)$
- General regularization strategies
  - Total variation, edge-preserving penalties
  - Constraints on reconstruction
  - Prior images and other prior knowledge

$$\Phi(\mu; y) = -L(\mu; y) + \beta R(\mu)$$

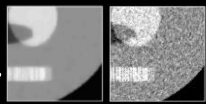
Indifferent to the specifics of the acquisition

- Sampling – sparse acquisitions, redundancy, etc.
- Geometry – helical vs. cone-beam vs. unusual geometries

New Capabilities and New Choices

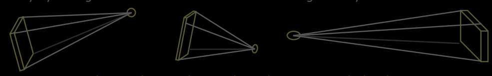
Fine control over regularization

- Various kinds of regularization — Which one?
- Regularization strength — How strong?
- More exotic controls — Space-variant designs?



Capability for new data acquisition schemes

- Fluence modulation — How to dynamically change mA?
- Sparse acquisitions — Which projections and how many?
- Arbitrary system geometries — What source-detector geometry is best?



The best answer depends on the task to be accomplished

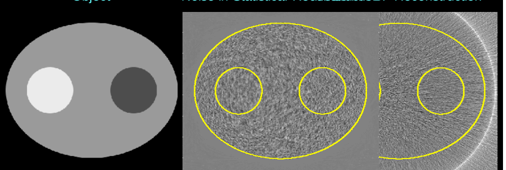
- What are you looking for?
- Where are you looking for it?
- How certain do you need to be?

Goal: Leverage capabilities associated with advanced model-based approaches for optimized task performance.

Image Properties in Adv. Recon.

Image properties (e.g., noise and spatial resolution) are

- Patient-dependent
- Contrast-dependent
- Position-dependent (nonstationary/space-variant)



For prospective decision making, image property prediction is needed

- What kind of image quality measures can we use?
- How do we contend with object-dependence?

Image Properties Prediction

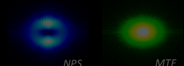
Accurate predictions of image quality will require anatomical knowledge

Increasing availability of anatomical information prior to scanning

- Longitudinal studies
  - disease progression
  - treatment assessments
- Interventional imaging
  - intraoperative imaging, IGRT
- Scout images in CT
  - 3D scouts, PA/lateral scouts
- Anatomical atlases (statistical atlases)

Care must be used in selecting appropriate image quality metrics

- Many advanced reconstruction methods are highly space-variant/nonstationary
  - More sophisticated regularization (prior images, etc.) has added difficulty
- Some methods exhibit locally space-invariant/stationary behavior permitting use of
  - Local noise power spectrum
  - Local modulation transfer function



Consider advanced reconstruction methods with local stationarity

- Penalized-likelihood reconstruction with (non-edge-preserving) quadratic penalty

Penalized-Likelihood Reconstruction

$$\bar{y} = \mathbf{D}\{b\}\exp(-\mathbf{A}\mu) \qquad L(\mu;y) = \sum_i y_i \log \bar{y}_i(\mu) - \bar{y}_i(\mu)$$

$$\hat{\mu} = \arg\min \Phi(\mu;y) = \arg\min\left(-L(\mu;y) + \beta\mu^T\mathbf{R}\mu\right)$$

Analysis is potentially difficult due implicit definition and nonlinearity

but approximate expressions for local covariance and local point spread function have been derived (Fessler, 1996)

$$[\mathrm{cov}\{\hat{\mu}\}]_{j\cdot} \approx \left[\mathbf{A}^T\mathbf{D}\{\bar{y}(\mu)\}\mathbf{A} + \beta\mathbf{R}\right]^{-1}\mathbf{A}^T\mathrm{cov}\{y\}\mathbf{A}\left[\mathbf{A}^T\mathbf{D}\{\bar{y}(\mu)\}\mathbf{A} + \beta\mathbf{R}\right]^{-1} e_j$$

Backprojector Regularizer + Strength Backprojector Measurement Covariance Projector Backprojector Regularizer + Strength j^{th} unit vector

$$PSF_j \approx \left[\mathbf{A}^T\mathbf{D}\{\bar{y}(\mu)\}\mathbf{A} + \beta\mathbf{R}\right]^{-1}\mathbf{A}^T\mathbf{D}\{\bar{y}(\mu)\}\mathbf{A}e_j$$

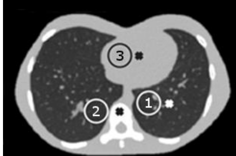
Backprojector Regularizer + Strength Backprojector Projector

Fessler and Rogers, "Spatial resolution properties of penalized-likelihood image recon.: Space-invariant tomographs" *Trans. Im. Proc.* 5(9), 1996.
Stayman and Fessler, "Efficient calculation of resolution and covariance for penalized-likelihood recon. in fully 3-D SPECT," *Trans. Med. Im.*, 23 (12), 2004.

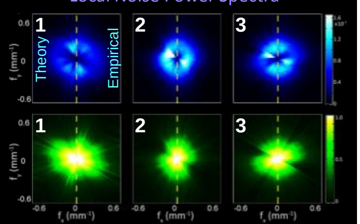
Noise & Resolution Prediction in PL

Geometry, Patient Anatomy, Location, Regularization Strength → Predictor → NPS, MTF → Task Performance

Local Noise Power Spectra



Patient Anatomy

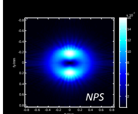


Local Modulation Transfer Functions

G. Gang, J. W. Stayman, W. Zbijewski, J. H. Siewerdsen, "Modeling and controlling nonstationary noise characteristics in filtered-backprojection and penalized-likelihood image reconstruction," *SPIE Medical Imaging*, Orlando, FL, Vol. 8668, February 2013.

Task-Based Detectability Index

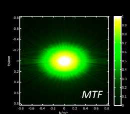
Detectability Index for a Non-Prewhitening Observer



Spatial Resolution

$$d_j'^2 = \frac{\left[\iiint \left(MTF_j \cdot W_{Task}\right)^2 df_x df_y df_z\right]^2}{\iiint NPS_j \cdot \left(MTF_j \cdot W_{Task}\right)^2 df_x df_y df_z}$$

Noise Imaging Task

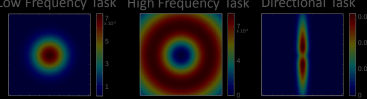


Imaging Task Function

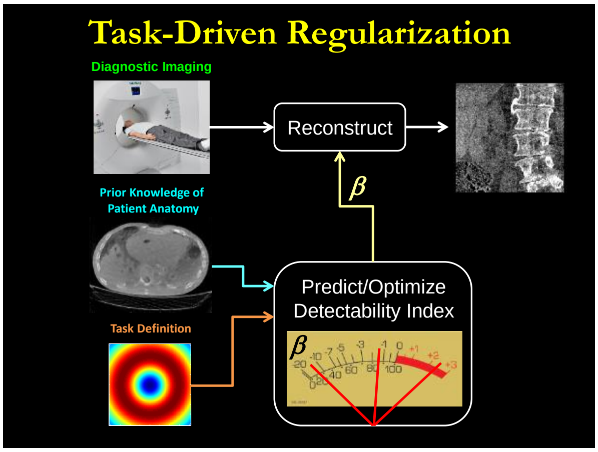
$$W_{Task} = H_1 - H_2$$

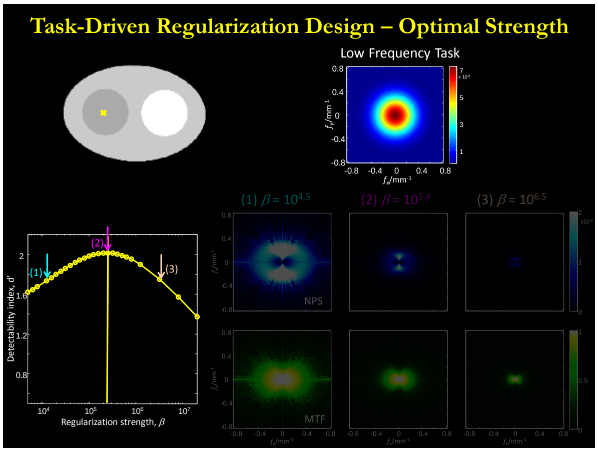
H_1: Stimulus present
H_2: Stimulus not present

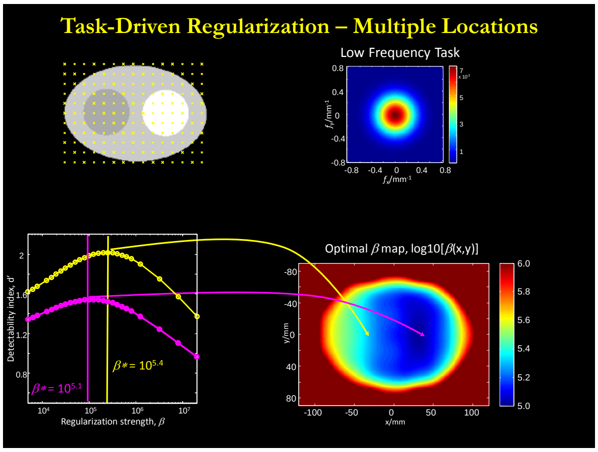
Low Frequency Task High Frequency Task Directional Task

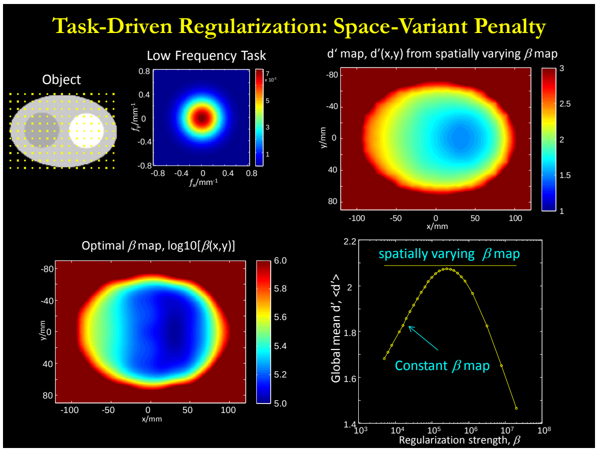


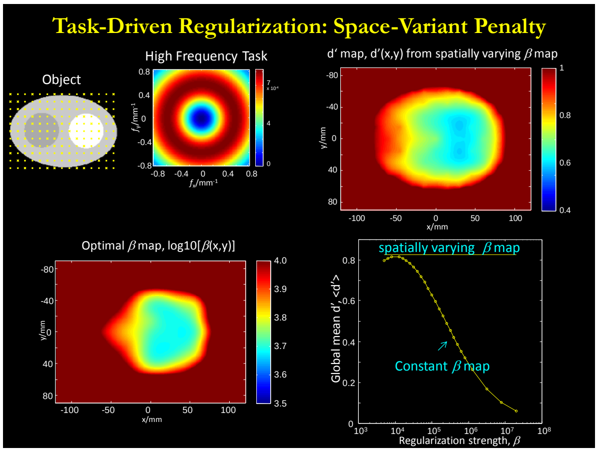
*ICRU54 "Medical imaging – the assessment of image quality"

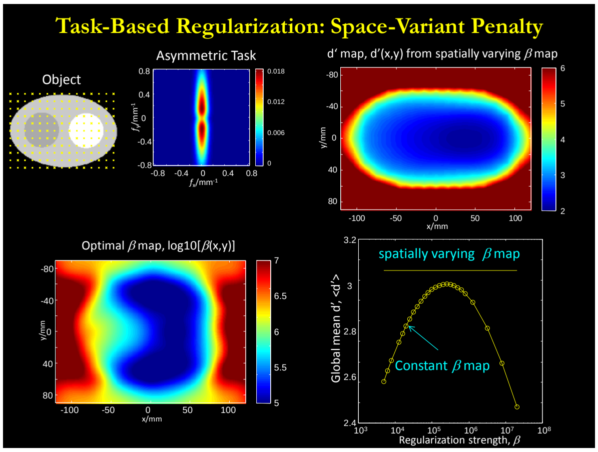

Task-Driven Regularization
Diagnostic Imaging
Reconstruct
β
Prior Knowledge of
Patient Anatomy
Predict/Optimize
Detectability Index
Task Definition

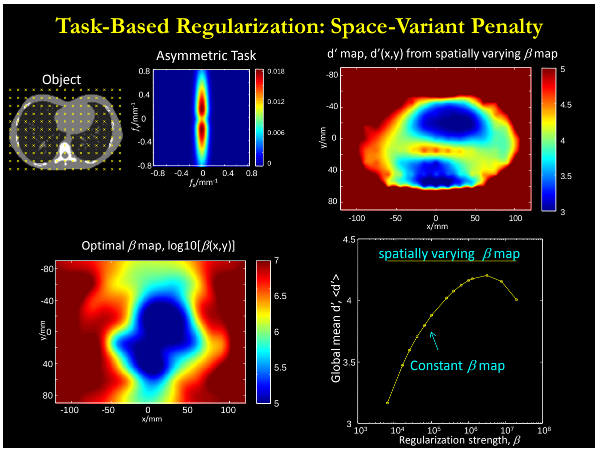

Task-Driven Regularization Design – Optimal Strength
Low Frequency Task
(1) $\beta = 10^{4.5}$
(2) $\beta = 10^{5.4}$
(3) $\beta = 10^{6.5}$
NPS
MTF
Detectability index, d'
Regularization strength, β

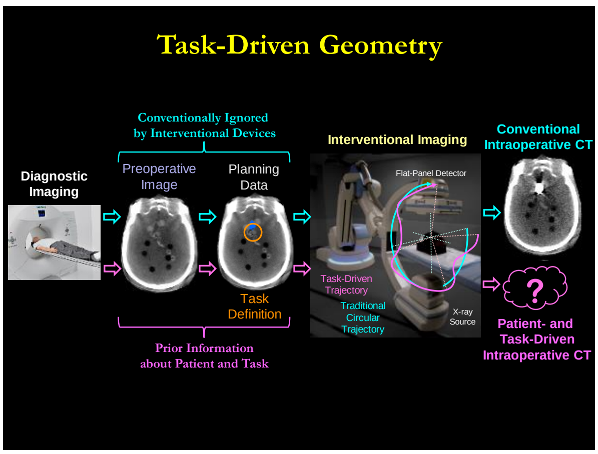

Task-Driven Regularization – Multiple Locations
Low Frequency Task
Optimal β map, log10[β(x,y)]
$\beta* = 10^{5.4}$
$\beta* = 10^{5.1}$
Detectability index, d'
Regularization strength, β
x/mm
y/mm

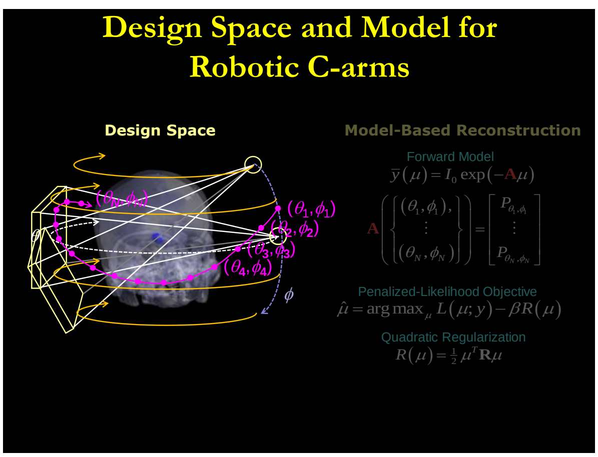

Task-Driven Regularization: Space-Variant Penalty
Object
Low Frequency Task
d' map, d'(x,y) from spatially varying β map
Optimal β map, log10[β(x,y)]
spatially varying β map
Constant β map
Global mean d', <d'>
Regularization strength, β
x/mm
y/mm


Task-Driven Regularization: Space-Variant Penalty
Object
High Frequency Task
d' map, d'(x,y) from spatially varying β map
Optimal β map, log10[β(x,y)]
spatially varying β map
Constant β map
Global mean d', <d'>
Regularization strength, β
x/mm
y/mm


Task-Based Regularization: Space-Variant Penalty
Object
Asymmetric Task
d' map, d'(x,y) from spatially varying β map
Optimal β map, log10[β(x,y)]
spatially varying β map
Constant β map
Global mean d', <d'>
Regularization strength, β
x/mm
y/mm


Task-Based Regularization: Space-Variant Penalty
Object
Asymmetric Task
d' map, d'(x,y) from spatially varying β map
Optimal β map, log10[β(x,y)]
spatially varying β map
Constant β map
Global mean d', <d'>
Regularization strength, β
x/mm
y/mm


Task-Driven Geometry
Conventionally Ignored
by Interventional Devices
Diagnostic
Imaging
Preoperative
Image
Planning
Data
Task
Definition
Prior Information
about Patient and Task
Interventional Imaging
Flat-Panel Detector
Task-Driven
Trajectory
Traditional
Circular
Trajectory
X-ray
Source
Conventional
Intraoperative CT
?
Patient- and
Task-Driven
Intraoperative CT


Design Space and Model for
Robotic C-arms
Design Space
Model-Based Reconstruction
Forward Model
$\bar{y}(\mu) = I_0 \exp(-\mathbf{A}\mu)$
Penalized-Likelihood Objective
$\hat{\mu} = \arg\max_{\mu} L(\mu; y) - \beta R(\mu)$
Quadratic Regularization
$R(\mu) = \frac{1}{2}\mu^T \mathbf{R} \mu$

Task-based Optimization of Geometry

Detectability Index (NPW Observer)

Spatial Resolution

$$d_j'^2 = \frac{\left[\iiint \left(MTF_j \cdot W_{Task}\right)^2 df_x df_y df_z\right]^2}{\iiint NPS_j \cdot \left(MTF_j \cdot W_{Task}\right)^2 df_x df_y df_z}$$

Noise Imaging Task

Predictors of Noise/Resolution for PLE

$$NPS_j \approx \frac{\mathcal{F}\left\{\mathbf{A}^T\mathbf{D}\{y(\mu)\}\mathbf{A}e_j\right\}}{\left|\mathcal{F}\left\{\mathbf{A}^T\mathbf{D}\{y(\mu)\}\mathbf{A}e_j + \beta\mathbf{R}e_j\right\}\right|^2}$$

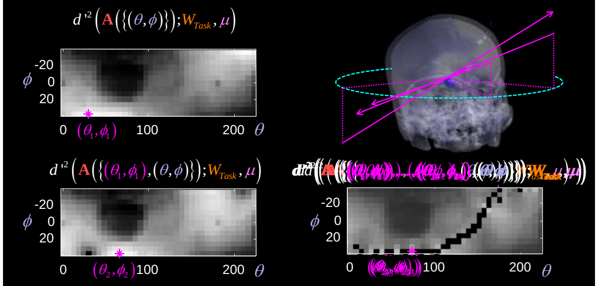
$$MTF_j \approx \frac{\mathcal{F}\left\{\mathbf{A}^T\mathbf{D}\{y(\mu)\}\mathbf{A}e_j\right\}}{\mathcal{F}\left\{\mathbf{A}^T\mathbf{D}\{y(\mu)\}\mathbf{A}e_j + \beta\mathbf{R}e_j\right\}}$$

Optimization

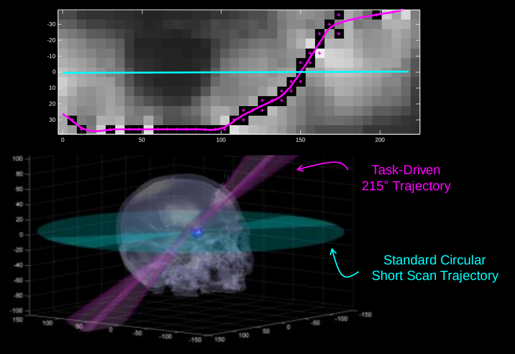
$$\cancel{\left(\hat{\Theta},\hat{\Phi}\right) = \arg\max_{\Theta,\Phi} d'^2\left(\mathbf{A}(\Theta,\Phi); W_{Task}, \mu\right)}$$

$$\left(\hat{\theta}_{N+1},\hat{\phi}_{N+1}\right) = \arg\max_{\theta,\phi} d'^2\left(\mathbf{A}\left(\{(\theta_1,\phi_1),\ldots,(\theta_N,\phi_N),(\theta,\phi)\}\right); W_{Task}, \mu\right)$$

Series of "Next Best View" Optimizations

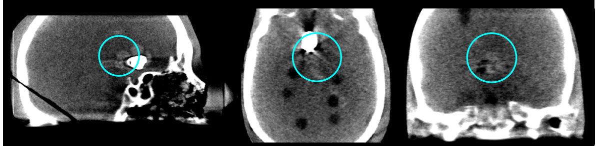


Task-Optimizated Trajectory

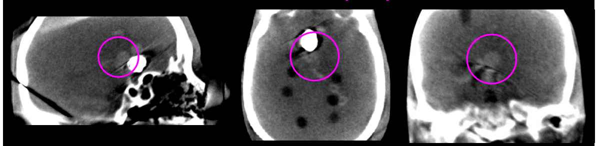


Reconstructions from Simulation Studies

Standard Circular Short Scan Trajectory



Task-Driven 215° Trajectory

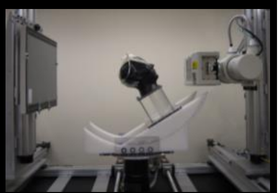


J. W. Stayman and J. H. Siewerdsen, "Task-Based Trajectories in Iteratively Reconstructed Interventional Cone-Beam CT," *Int'l Mtg. Fully 3D Image Recon. in Radiology and Nuc. Med.*, Lake Tahoe, June 16-21, 2013.

Testbench Investigations

Anthropomorphic Head Phantom and Synthetic Vasculature

Modified CBCT Testbench with Tilt Platform

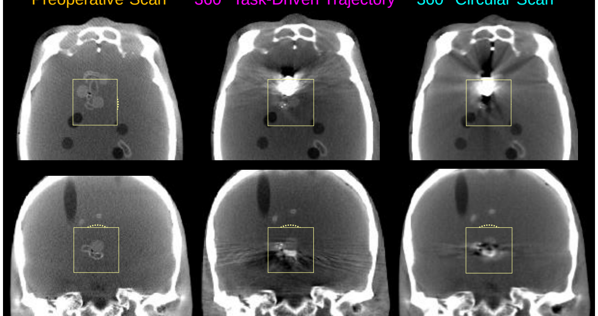


Ability to step through entire embolization workflow

- Initial CT for diagnosis and sizing of coils/stents
- Intraoperative flouroscopy for coil embolization
- Post-operative C-arm CT for assessment

Testbench Reconstructions

Preoperative Scan | 360° Task-Driven Trajectory | 360° Circular Scan



Conclusions

Presented a general framework for task-driven imaging using advanced reconstruction methods whereby one can optimize
- *Regularization
- *Acquisition geometry
- Fluence modulation – automatic exposure control, fluence field modulation
- Sparse acquisitions
- Dose constraints

New paradigm for patient-specific and task-specific imaging
- Customization of both acquisition and reconstruction

Lots of unanswered questions (aka Future Work)
- Predictors for highly space-variant systems
- Optimization using generalized task functions (beyond detectability)
- How to quantify performance with prior image techniques (and other advanced methods)