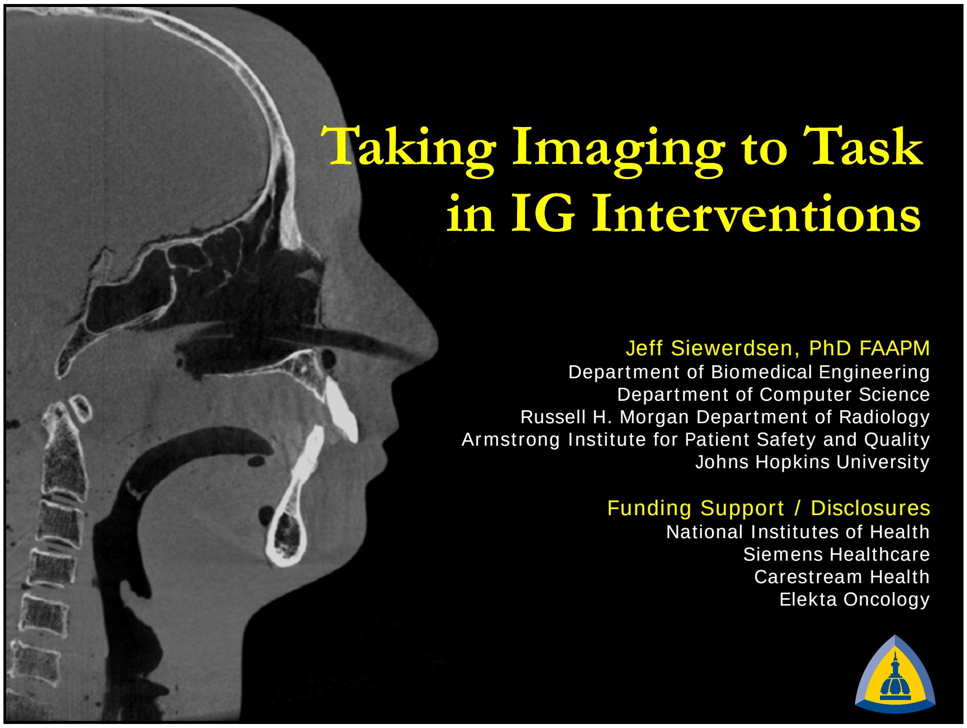

Taking Imaging to Task in IG Interventions
Jeff Siewerdsen, PhD FAAPM
Department of Biomedical Engineering
Department of Computer Science
Russell H. Morgan Department of Radiology
Armstrong Institute for Patient Safety and Quality
Johns Hopkins University
Funding Support / Disclosures
National Institutes of Health
Siemens Healthcare
Carestream Health
Elekta Oncology

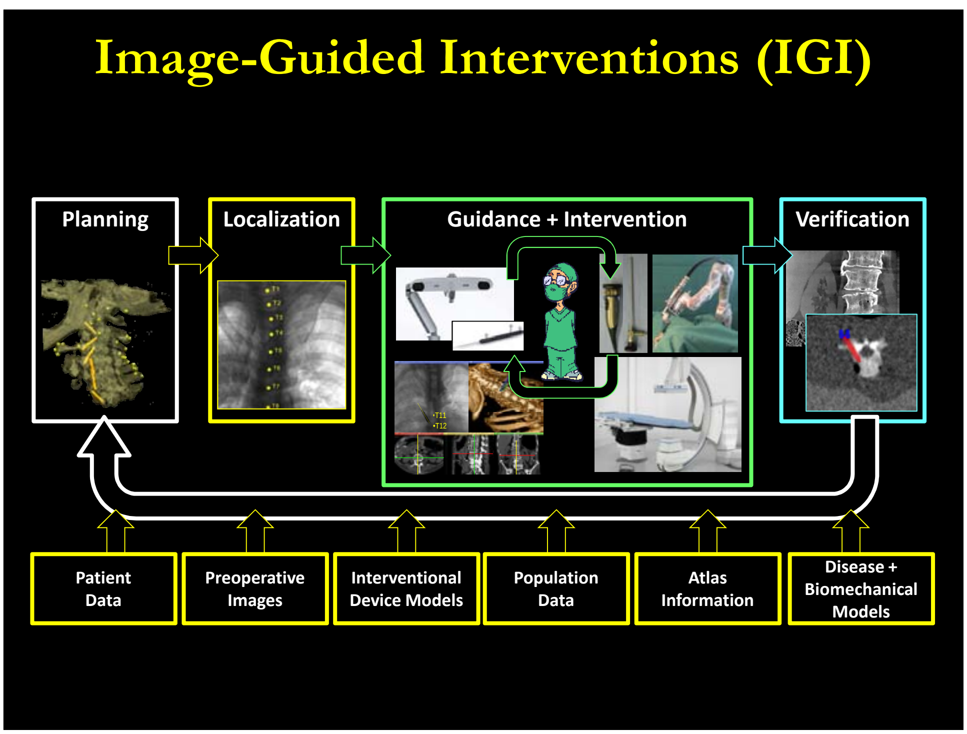
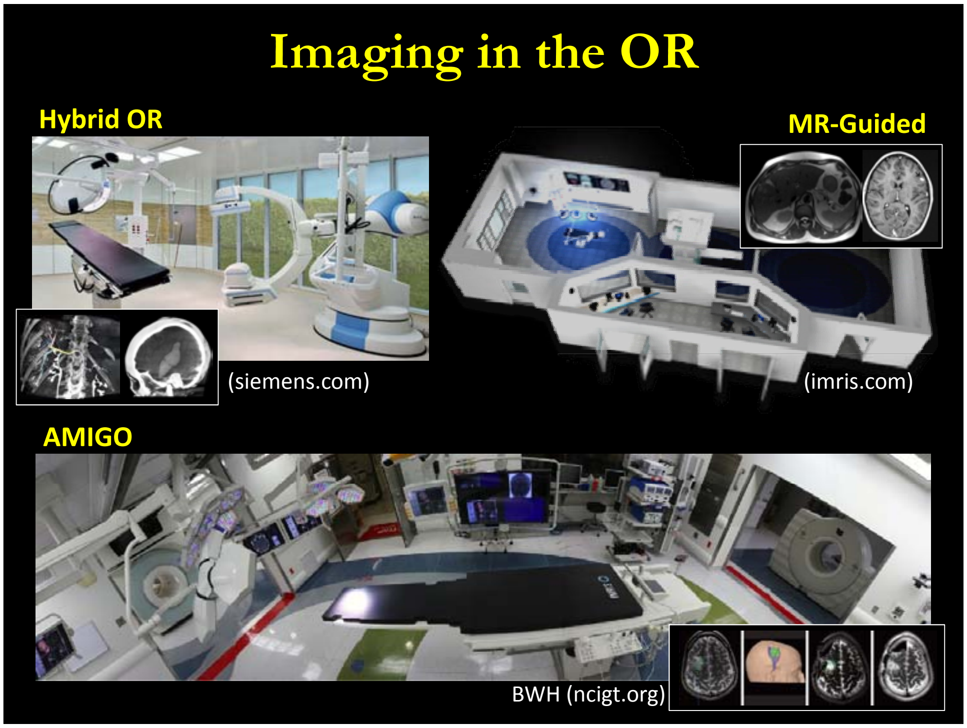
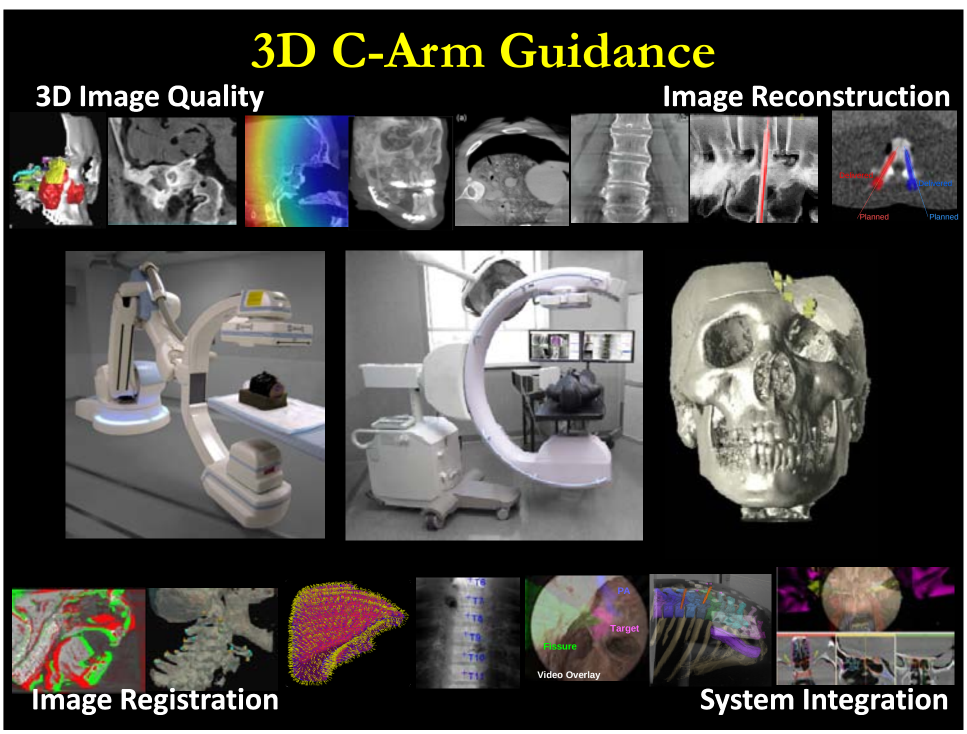
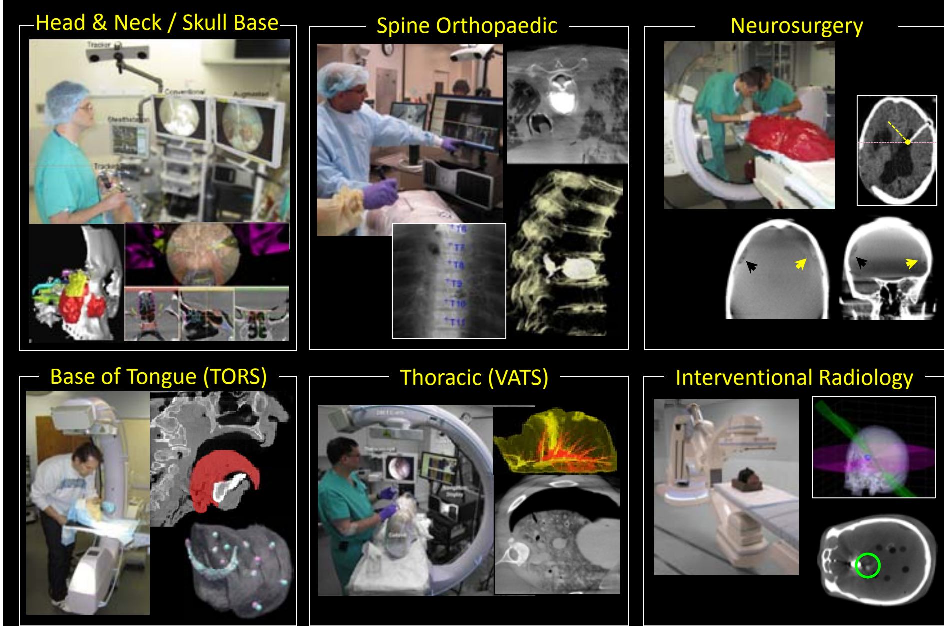


Image-Guided Interventions (IGI)
Planning
Localization
Guidance + Intervention
Verification
Patient Data
Preoperative Images
Interventional Device Models
Population Data
Atlas Information
Disease + Biomechanical Models


Imaging in the OR
Hybrid OR
(siemens.com)
MR-Guided
(imris.com)
AMIGO
BWH (ncigt.org)


3D C-Arm Guidance
3D Image Quality
Image Reconstruction
Planned
Planned
Target
Fissure
Video Overlay
Image Registration
System Integration

## CBCT-Guided Interventions




## Taking Imaging to Task


**Patient-specific priors**
- Preoperative images (CT, MR, PET)
- Planning information (trajectories and volume definitions)
- Intraoperative images (2D, 3D, multi-modality)

**Procedure-specific priors**
- Interventional devices

**Population, statistical, and model-based priors**
- Atlases

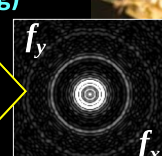
**Specification of the *imaging task***
- Size, Spatial frequency content
- Contrast, Location

→ **Statistical Decision Theory (Hypothesis Testing)**

Hypothesis 1 $H_1(x)$

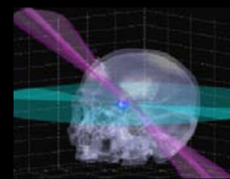
Hypothesis 2 $H_2(x)$

$$\left|F\left[H_1(x) - H_2(x)\right]\right|$$




Task Function $W_{task}(f)$

# Learning Objectives



**Understand how a specification of <u>imaging task</u> can be leveraged to drive the imaging process**
- Task-based detectability → Design, optimization
- Task-driven imaging

**Understand how <u>model-based image reconstruction</u> can propel application in IGI**
- Improve image quality, reduce dose
- Use of prior information


**Understand how intraoperative imaging offers not only a means of high-precision guidance, but also a system for improved <u>safety and quality assurance.</u>**
- Streamlined workflow
- Localization, verification
- Independent checks, QA

# Image Quality

# Image Quality… and Imaging Task

**Detectability Index (*d'*)**

Prewhitening observer (PW)

Spatial Resolution

$$d'^2 = \iiint \frac{MTF^2(f)}{NPS(f)} W_{task}^2 \, df$$

Image Noise

Imaging Task

Dose
Detector Configuration
Sampling
Electronic Noise

Detection
Discrimination
Classification

ICRU Report #54

# Image Quality… and Imaging Task

**Detectability Index (*d'*)**

Prewhitening observer (PW)
Generalized (include anatomical background etc.)
Non-prewhitening observer (NPW)
Anthropomorphic (e.g., eye filter, NPWEi)

Eye Filter
Internal Noise

$$d'^2 = \frac{\left[\iiint MTF^2(f) W_{task}^2 E^4(f)\, df\right]^2}{\iiint \left[S_Q(f) + S_E(f) + S_B(f)\right] MTF^2(f) W_{task}^2 E^4(f) + N_{int}\, df}$$

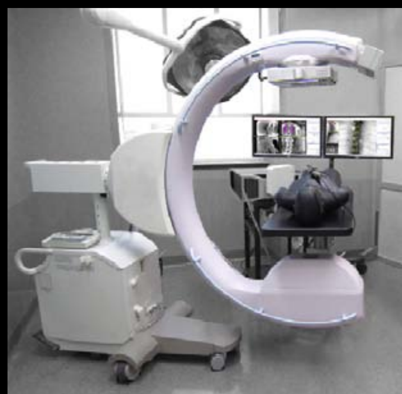
Quantum Noise
Electronic Noise

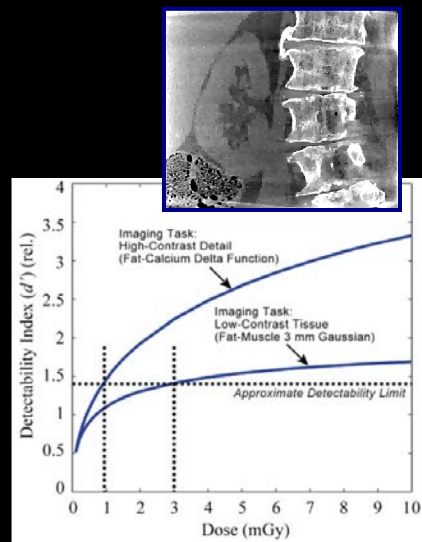
Anatomical
Background

ICRU Report #54
Burgess et al., JOSA A (14) 1997
Wagner et al. Med Phys (4) 1977
also papers by Richard, Tward, Prakash, Gang (Med Phys 2005-13)

# Detectability Index

**Example Application: Task-Based *Technique Selection***






Siewerdsen, NIM Phys. Rev. A (2012)

# Model-Based CBCT Reconstruction

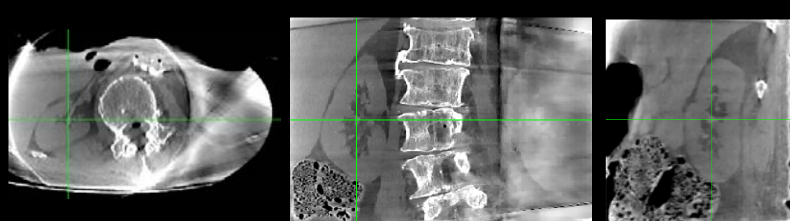
**Soft-Tissue Imaging**

Fresh cadaver (non-fixed)

PL + Huber Penalty (PLH) vs FBP

Recon parameters for *matched* resolution

- 80 HU contrast
- ESF width σ = 1 mm

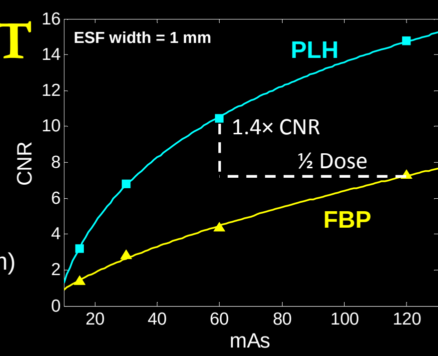


Wang et al. PMB (in review)

# Model-Based CBCT Reconstruction

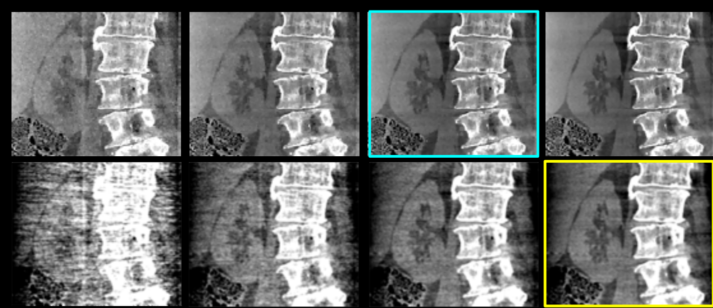
### Low Dose Comparison

100 kVp (15 – 120 mAs)
PLH reconstruction
- Matched spatial resolution ($\sigma_{ESF}$ = 1 mm)
- Reduces noise
- Preserves high contrast structures




PLH

FBP



Wang et al. PMB (in review) 15 mAs 30 mAs 60 mAs 120 mAs

# Model-Based Image Reconstruction

For example: Penalized Likelihood (PL) Estimation

An objective function (L) with a roughness penalty (R) on noisy data:
- Improves low-dose image quality, robust to limited (sparse) data
- Numerous iterative algorithms to solve the objective:
  - EM, ordered subsets, paraboloidal surrogates, …

Log-Likelihood $L(\vec{g},\vec{\mu}) = \ln p(\vec{g} \mid \vec{\mu})$

Measured Projections

$$\hat{\vec{\mu}} = \arg\max_{\vec{\mu}} L(\vec{g},\vec{\mu}) - \beta R(\vec{\mu})$$

Balances data fidelity versus the penalty

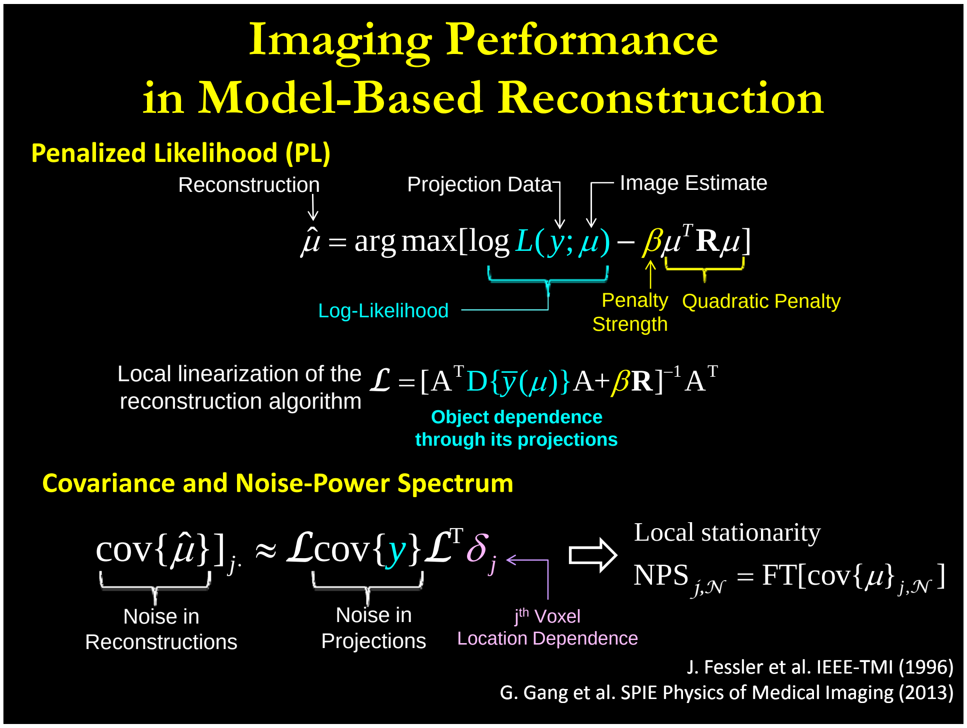
Regularization / Penalty

Image Estimate

Difference in voxel values

$$R(\vec{\mu}) = \sum_j \sum_{k \in \mathcal{N}_j} \psi(\mu_j - \mu_k)$$

Penalty function (e.g., linear, quadratic, Huber, …)


Imaging Performance
in Model-Based Reconstruction
Penalized Likelihood (PL)
Reconstruction
Projection Data
Image Estimate
$\hat{\mu} = \arg\max[\log L(y;\mu) - \beta\mu^T \mathbf{R}\mu]$
Log-Likelihood
Penalty Strength
Quadratic Penalty
Local linearization of the reconstruction algorithm
$\mathcal{L} = [\mathrm{A}^{\mathrm{T}}\mathrm{D}\{\bar{y}(\mu)\}\mathrm{A} + \beta\mathbf{R}]^{-1}\mathrm{A}^{\mathrm{T}}$
Object dependence through its projections
Covariance and Noise-Power Spectrum
$\mathrm{cov}\{\hat{\mu}\}]_{j\cdot} \approx \mathcal{L}\mathrm{cov}\{y\}\mathcal{L}^{\mathrm{T}}\delta_j$
Noise in Reconstructions
Noise in Projections
j[th] Voxel Location Dependence
Local stationarity
$\mathrm{NPS}_{j,\mathcal{N}} = \mathrm{FT}[\mathrm{cov}\{\mu\}_{j,\mathcal{N}}]$
J. Fessler et al. IEEE-TMI (1996)
G. Gang et al. SPIE Physics of Medical Imaging (2013)

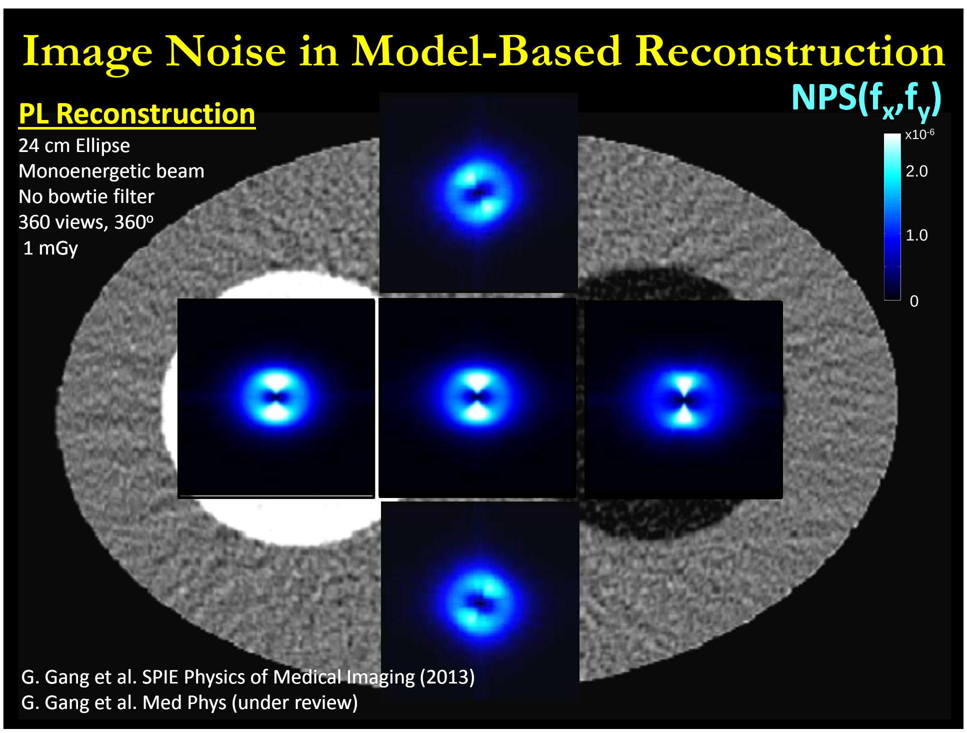


Image Noise in Model-Based Reconstruction
PL Reconstruction
24 cm Ellipse
Monoenergetic beam
No bowtie filter
360 views, 360°
1 mGy
$\mathrm{NPS}(f_x,f_y)$
x10^-6
2.0
1.0
0
G. Gang et al. SPIE Physics of Medical Imaging (2013)
G. Gang et al. Med Phys (under review)

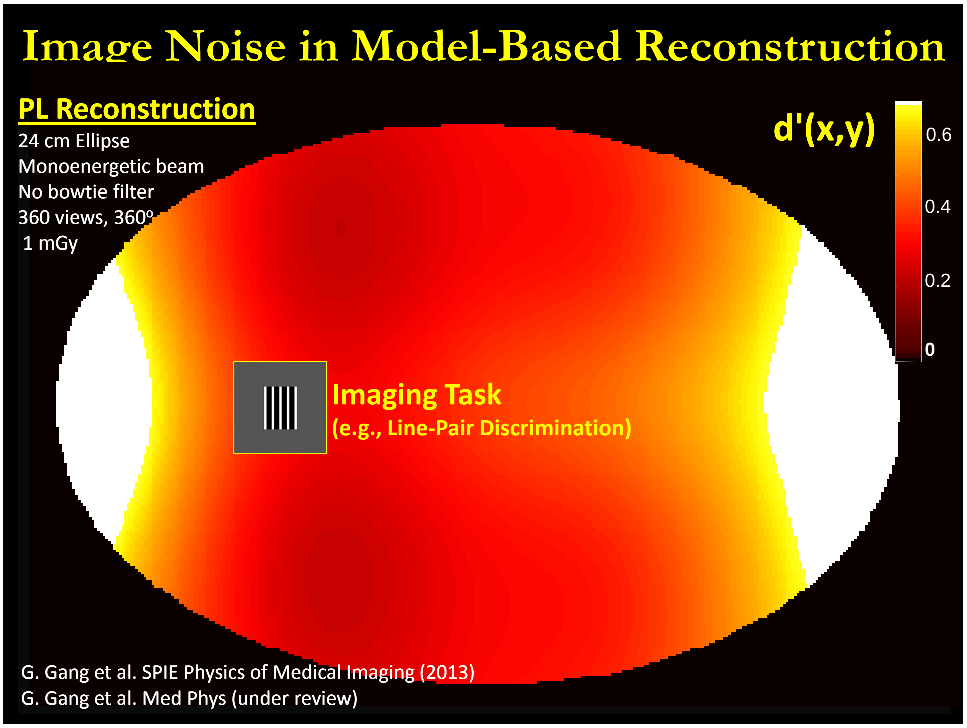
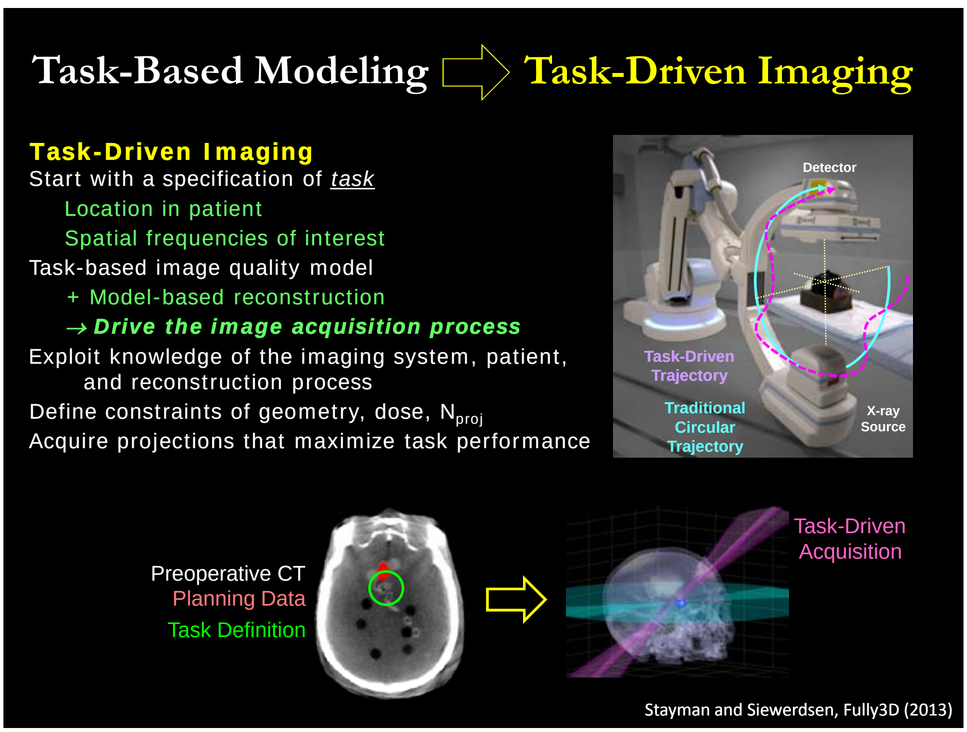


Image Noise in Model-Based Reconstruction
PL Reconstruction
24 cm Ellipse
Monoenergetic beam
No bowtie filter
360 views, 360º
1 mGy
d'(x,y)
0.6
0.4
0.2
0
Imaging Task
(e.g., Line-Pair Discrimination)
G. Gang et al. SPIE Physics of Medical Imaging (2013)
G. Gang et al. Med Phys (under review)


Task-Based Modeling
Task-Driven Imaging
Task-Driven Imaging
Start with a specification of task
Location in patient
Spatial frequencies of interest
Task-based image quality model
+ Model-based reconstruction
→ Drive the image acquisition process
Exploit knowledge of the imaging system, patient, and reconstruction process
Define constraints of geometry, dose, $N_{proj}$
Acquire projections that maximize task performance
Detector
Task-Driven Trajectory
Traditional Circular Trajectory
X-ray Source
Preoperative CT
Planning Data
Task Definition
Task-Driven Acquisition
Stayman and Siewerdsen, Fully3D (2013)

# Task-Driven Imaging

Detectability Index (*d'*) and Trajectory (Ω)

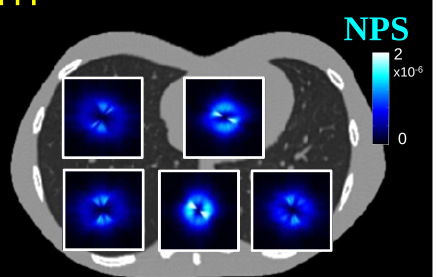
$$d_j'^2(\Omega,\mu) = \frac{\left[\iiint \left(MTF_j(\Omega)\cdot W_{Task}\right)^2 df_x df_y df_z\right]^2}{\iiint NPS_j(\Omega)\cdot\left(MTF_j(\Omega)\cdot W_{Task}\right)^2 df_x df_y df_z}$$

$$\Omega = \left\{\{\theta_1,\phi_1\},\cdots,\{\theta_N,\phi_N\}\right\}$$

Local Predictor of NPS and MTF

$$\mathrm{NPS}_{\mathcal{N}} = \mathrm{FT}[\mathrm{cov}\{\mu\}_{j,\mathcal{N}}]$$

$$\mathrm{MTF}_{\mathcal{N}} = \mathrm{FT}[\mathrm{PSF}\{\mu\}_{j,\mathcal{N}}]$$




Stayman and Siewerdsen, Fully3D (2013)

# Task-Driven Imaging

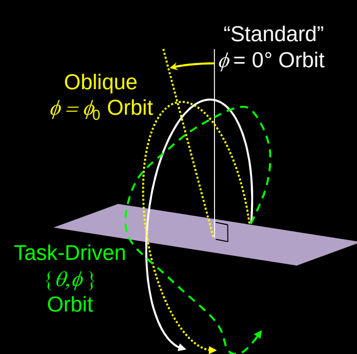
Detectability Index (*d'*) and Trajectory (Ω)

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

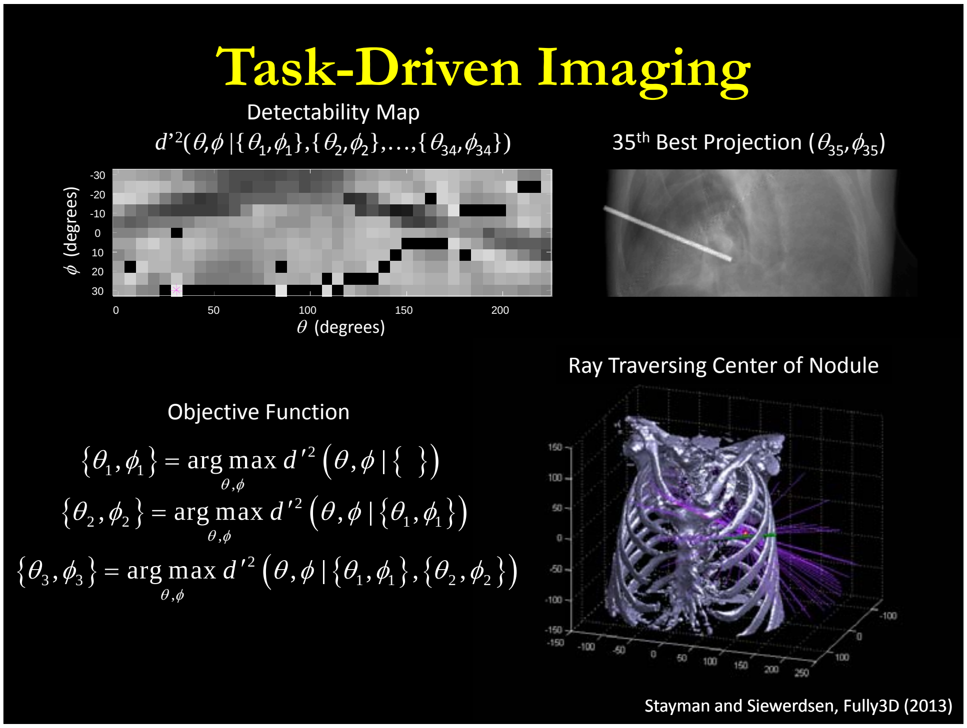
$$\Omega = \left\{\{\theta_1,\phi_1\},\cdots,\{\theta_N,\phi_N\}\right\}$$

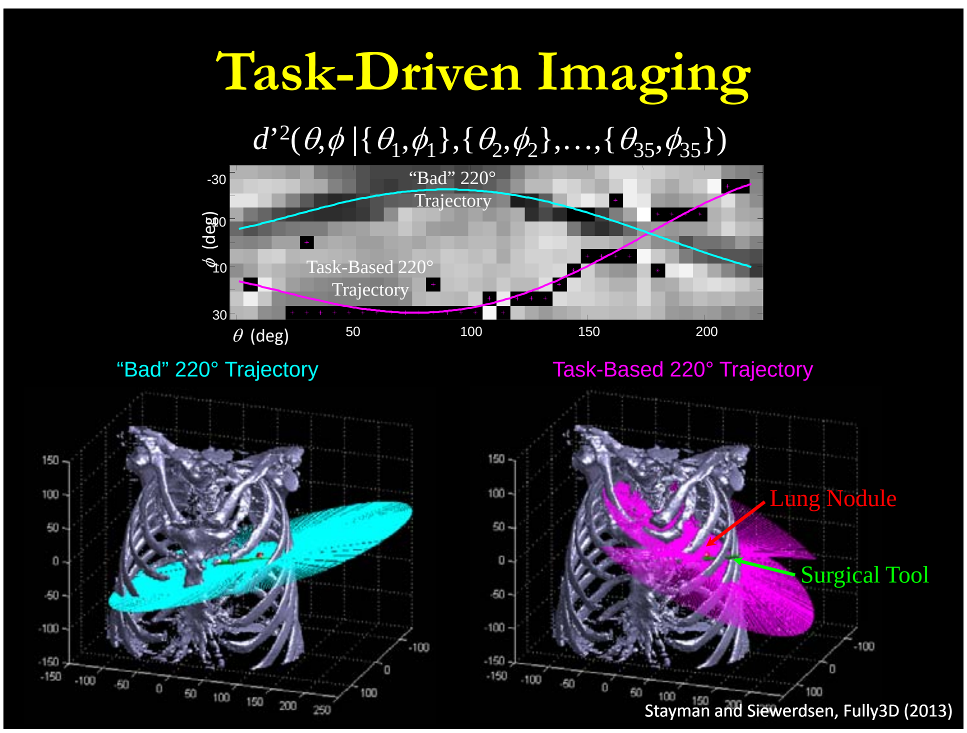
Design Goal

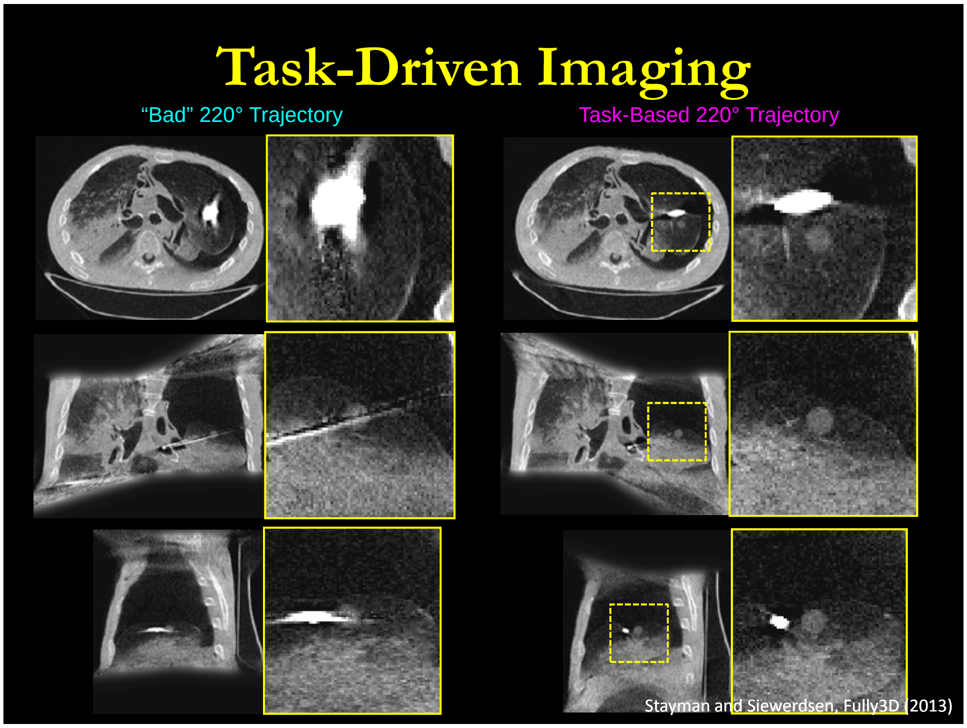
$$\hat{\Omega} = \arg\max_{\Omega} d_j'^2(\Omega,\mu)$$

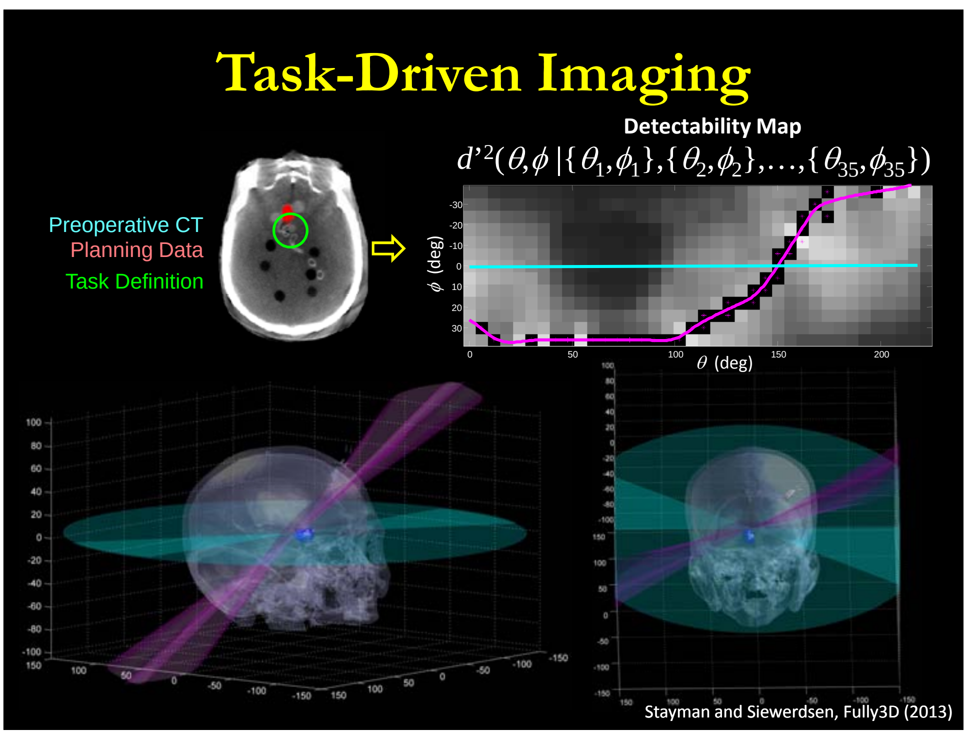


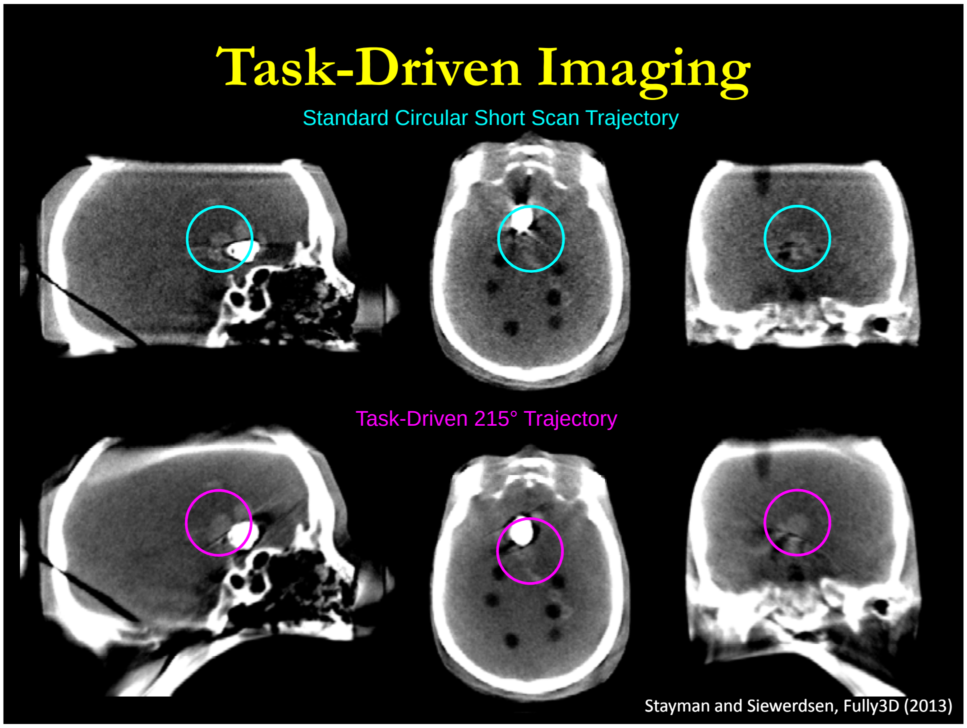

Stayman and Siewerdsen, Fully3D (2013)

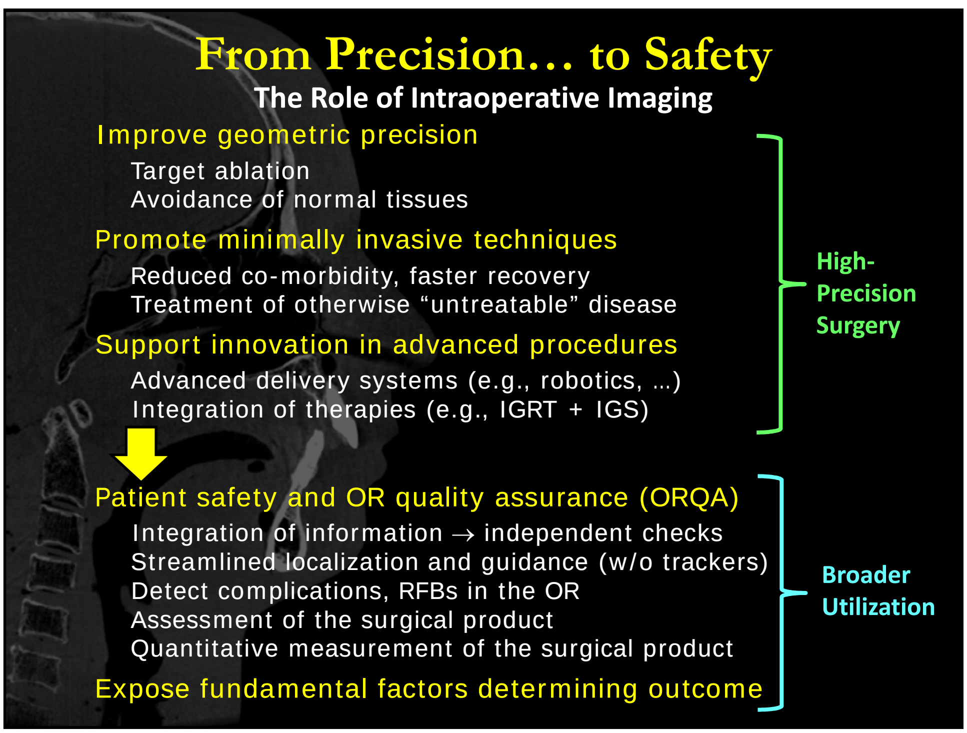

Task-Driven Imaging
Detectability Map
$d'^2(\theta,\phi\,|\,\{\theta_1,\phi_1\},\{\theta_2,\phi_2\},\ldots,\{\theta_{34},\phi_{34}\})$
$\phi$ (degrees)
$\theta$ (degrees)
35th Best Projection ($\theta_{35},\phi_{35}$)
Ray Traversing Center of Nodule
Objective Function
$\{\theta_1,\phi_1\} = \arg\max_{\theta,\phi} d'^2(\theta,\phi\,|\,\{\ \})$
$\{\theta_2,\phi_2\} = \arg\max_{\theta,\phi} d'^2(\theta,\phi\,|\,\{\theta_1,\phi_1\})$
$\{\theta_3,\phi_3\} = \arg\max_{\theta,\phi} d'^2(\theta,\phi\,|\,\{\theta_1,\phi_1\},\{\theta_2,\phi_2\})$
Stayman and Siewerdsen, Fully3D (2013)

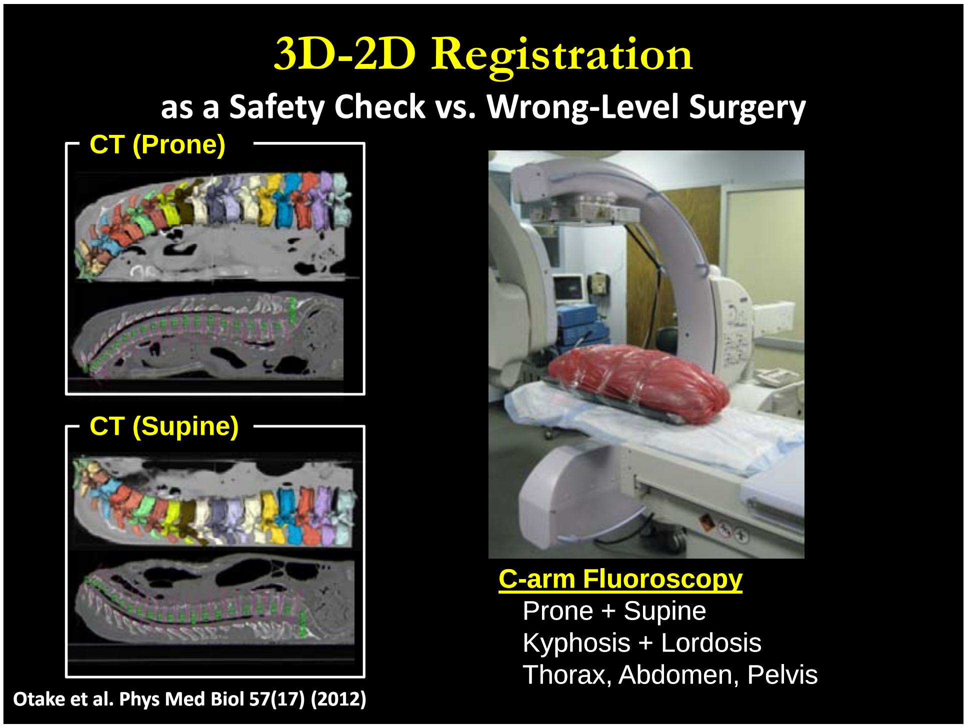

Task-Driven Imaging
$d'^2(\theta,\phi\,|\,\{\theta_1,\phi_1\},\{\theta_2,\phi_2\},\ldots,\{\theta_{35},\phi_{35}\})$
"Bad" 220° Trajectory
Task-Based 220° Trajectory
$\phi$ (deg)
$\theta$ (deg)
"Bad" 220° Trajectory
Task-Based 220° Trajectory
Lung Nodule
Surgical Tool
Stayman and Siewerdsen, Fully3D (2013)

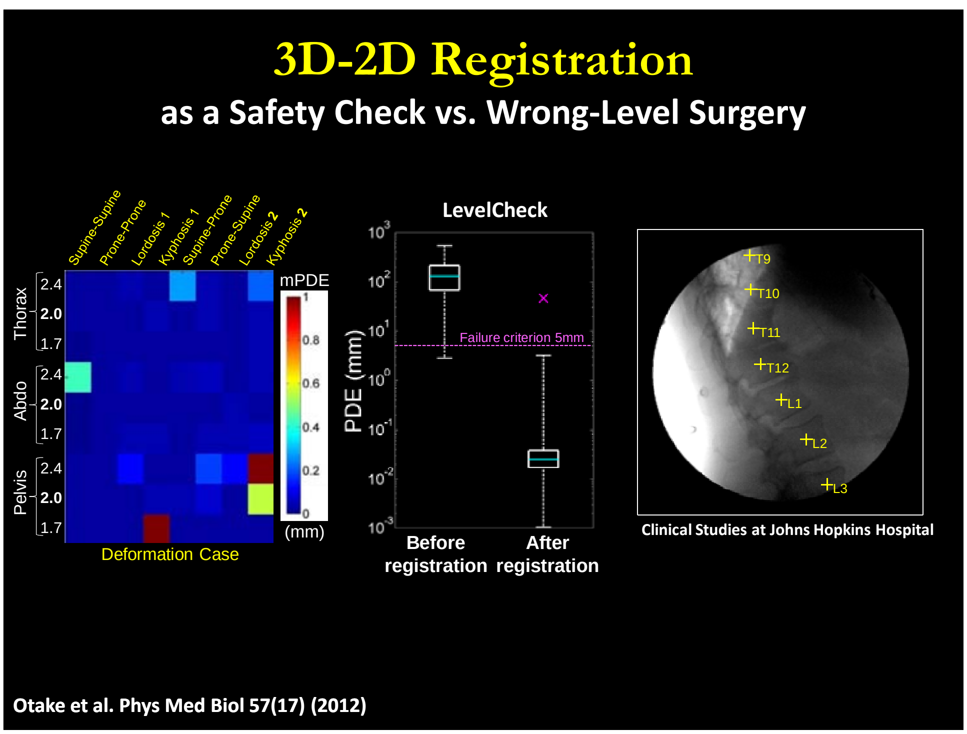

Task-Driven Imaging
"Bad" 220° Trajectory
Task-Based 220° Trajectory
Stayman and Siewerdsen, Fully3D (2013)

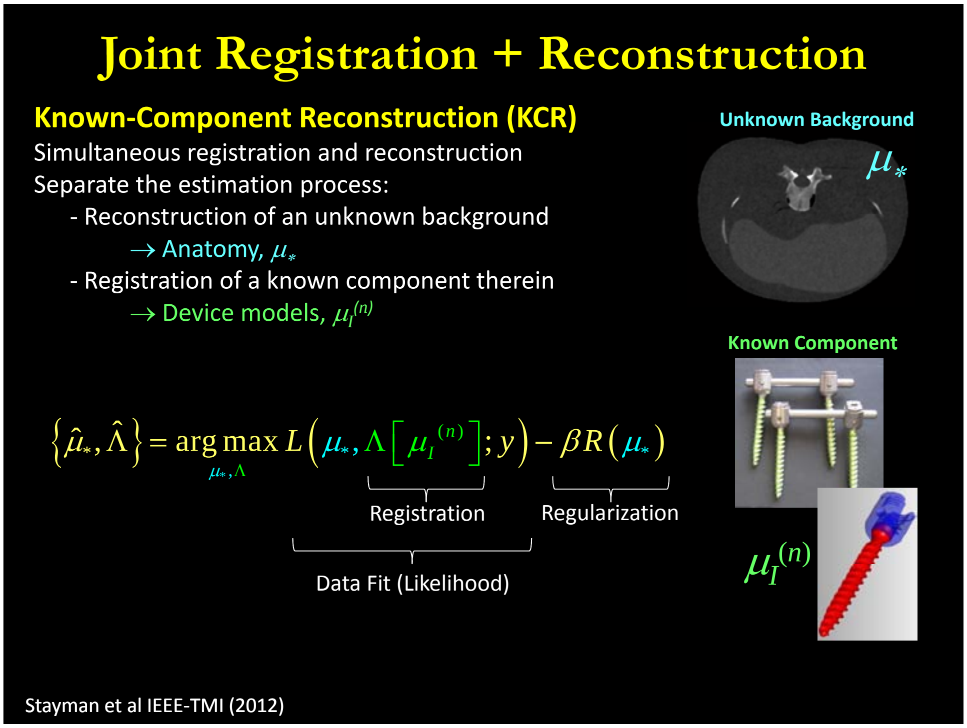

Task-Driven Imaging
Detectability Map
$d'^2(\theta,\phi\,|\{\theta_1,\phi_1\},\{\theta_2,\phi_2\},\ldots,\{\theta_{35},\phi_{35}\})$
Preoperative CT
Planning Data
Task Definition
$\phi$ (deg)
$\theta$ (deg)
Stayman and Siewerdsen, Fully3D (2013)

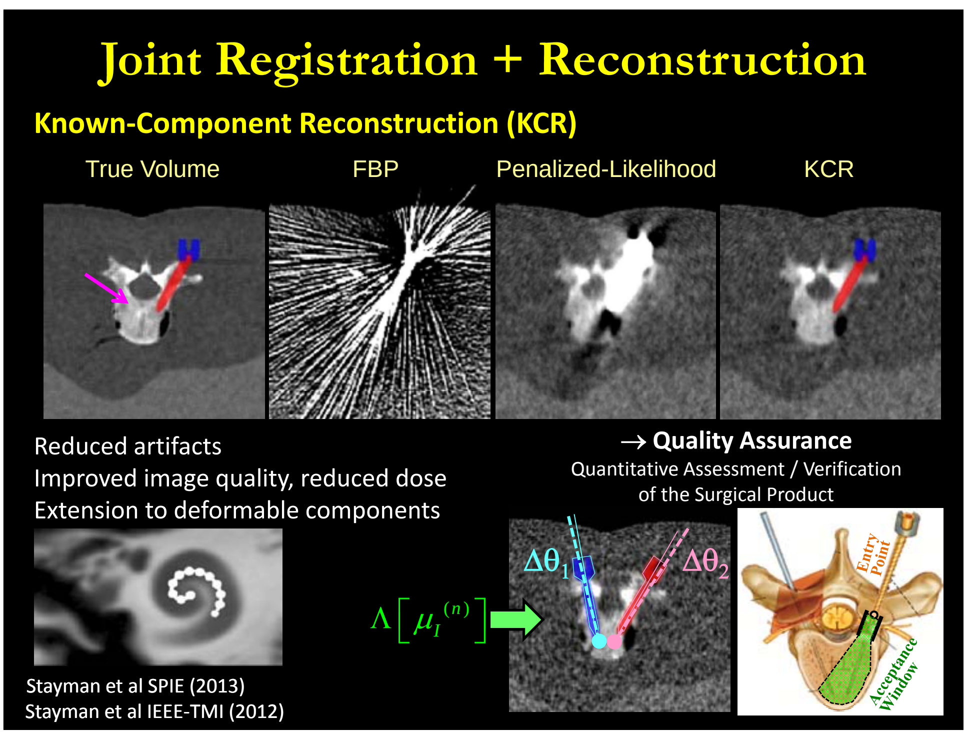

Task-Driven Imaging
Standard Circular Short Scan Trajectory
Task-Driven 215° Trajectory
Stayman and Siewerdsen, Fully3D (2013)


From Precision… to Safety
The Role of Intraoperative Imaging
Improve geometric precision
Target ablation
Avoidance of normal tissues
Promote minimally invasive techniques
Reduced co-morbidity, faster recovery
Treatment of otherwise “untreatable” disease
Support innovation in advanced procedures
Advanced delivery systems (e.g., robotics, …)
Integration of therapies (e.g., IGRT + IGS)
High-Precision Surgery
Patient safety and OR quality assurance (ORQA)
Integration of information → independent checks
Streamlined localization and guidance (w/o trackers)
Detect complications, RFBs in the OR
Assessment of the surgical product
Quantitative measurement of the surgical product
Expose fundamental factors determining outcome
Broader Utilization

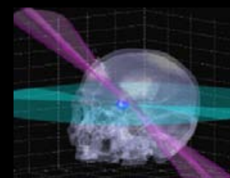

3D-2D Registration
as a Safety Check vs. Wrong-Level Surgery
CT (Prone)
CT (Supine)
C-arm Fluoroscopy
Prone + Supine
Kyphosis + Lordosis
Thorax, Abdomen, Pelvis
Otake et al. Phys Med Biol 57(17) (2012)


3D-2D Registration
as a Safety Check vs. Wrong-Level Surgery
Supine-Supine
Prone-Prone
Lordosis 1
Kyphosis 1
Supine-Prone
Prone-Supine
Lordosis 2
Kyphosis 2
Thorax
Abdo
Pelvis
mPDE
(mm)
Deformation Case
LevelCheck
PDE (mm)
Failure criterion 5mm
Before registration
After registration
T9
T10
T11
T12
L1
L2
L3
Clinical Studies at Johns Hopkins Hospital
Otake et al. Phys Med Biol 57(17) (2012)


Joint Registration + Reconstruction
Known-Component Reconstruction (KCR)
Simultaneous registration and reconstruction
Separate the estimation process:
- Reconstruction of an unknown background
→ Anatomy, $\mu_*$
- Registration of a known component therein
→ Device models, $\mu_I^{(n)}$
Unknown Background
$\mu_*$
Known Component
$\mu_I^{(n)}$
$\{\hat{\mu}_*, \hat{\Lambda}\} = \arg\max_{\mu_*,\Lambda} L(\mu_*, \Lambda[\mu_I^{(n)}]; y) - \beta R(\mu_*)$
Registration
Regularization
Data Fit (Likelihood)
Stayman et al IEEE-TMI (2012)


Joint Registration + Reconstruction
Known-Component Reconstruction (KCR)
True Volume
FBP
Penalized-Likelihood
KCR
Reduced artifacts
Improved image quality, reduced dose
Extension to deformable components
→ Quality Assurance
Quantitative Assessment / Verification
of the Surgical Product
$\Lambda[\mu_I^{(n)}]$
$\Delta\theta_1$
$\Delta\theta_2$
Entry Point
Acceptance Window
Stayman et al SPIE (2013)
Stayman et al IEEE-TMI (2012)

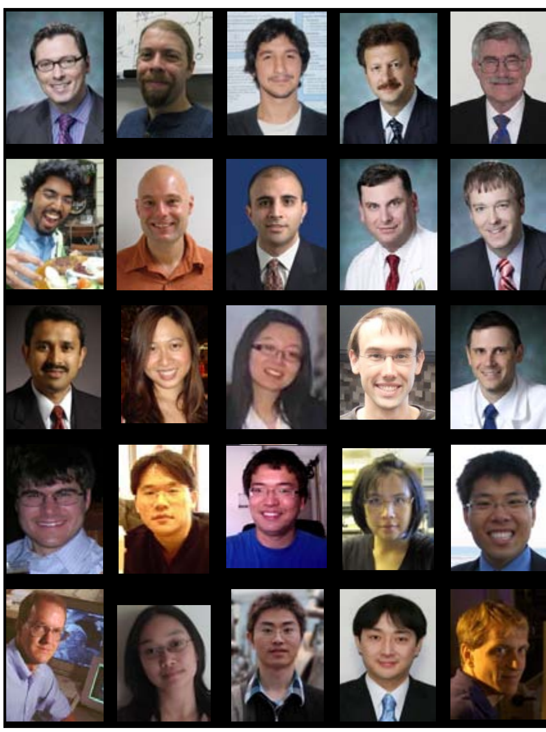
# Learning Objectives



Understand how a specification of imaging task can be leveraged to drive the imaging process
→ *Task-driven imaging*

Understand how model-based image reconstruction can propel application in IGI
→ *Penalized likelihood estimation (PLH)*
→ *Joint registration-reconstruction (KCR)*


Understand how intraoperative imaging offers not only a means of high-precision guidance, but also a system for improved safety and quality assurance.
→ *3D2D registration (LevelCheck)*
→ *Verification of surgical product (ORQA)*




# Acknowledgments

**I-STAR Laboratory**
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www.jhu.edu/istar

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Gary Gallia (Neurosurgery)
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Jeremy Richmon (Otolaryngology)
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John Carrino (MSK Radiology)
Peter Pronovost (Armstrong Institute)

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Hao Dang, Steve Tilley

**ECE**
Jerry Prince

**Comp Sci**
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Greg Hager
Ali Uneri
Dan Mirota
Sureerat Reaungamornrat

**Rad Onc**
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Junghoon Lee

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