AAPM 2014

Challenges and opportunities in assessment of image quality

Ehsan Samei
Department of Radiology
Duke University Medical Center

Disclosures

- Research grant: NIH R01 EB001838
- Research grant: General Electric
- Research grant: Siemens Medical
- Research grant: Carestream Health

Credits

Jeff Siewerdsen, Johns Hopkins
Grace Gang, Johns Hopkins
Guanghong Chen, UW
Ke Li, UW

CARL E. RAVIN ADVANCED IMAGING LABORATORIES

Duke CIPG
Clinical Imaging Physics Group

Imaging quality and safety

- Quality: Imaging provides a clinical benefit
  - Diagnostic information
  - Image quality: Universally-appreciated
  - Enhancement dependent on illusive criteria
- Safety: Imaging involves a level of "cost"
  - Monitory cost
  - Information excess
  - Radiation cost

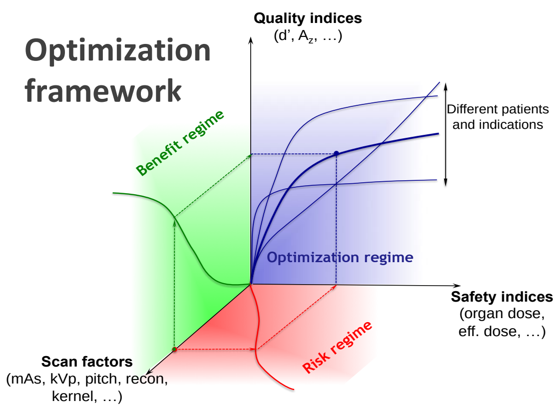
Optimization involves 4 steps:

1. Reasonable measures of risk
2. Reasonable measures of image quality
3. Justified balance between the two by targeted adjustment of system parameters
4. Consistent implementation

We cannot optimize imaging without quantification

1. The "risk"
2. The "benefit"
3. The "balance"

Optimization framework



Outline

1. Quality Characterization
2. Quality assessment
3. Quality implementation

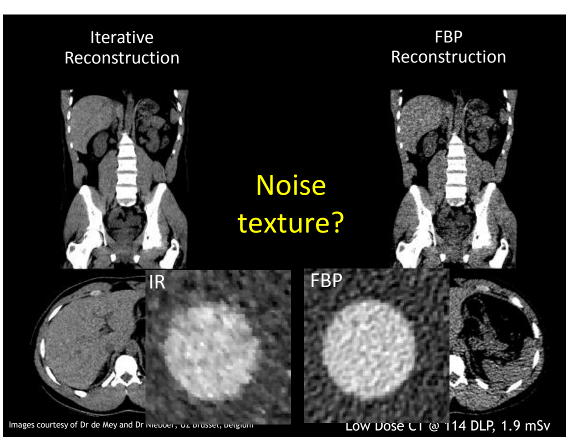
Model-based recons +s

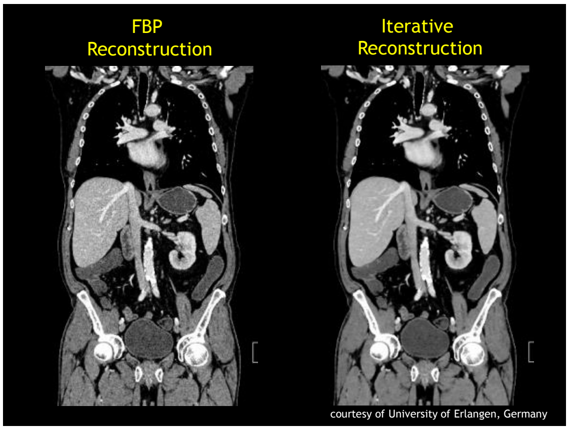
- Decades in the making
- Enabled by high-powered computers
- Significant potential for dose reduction
- Potential for improved image quality

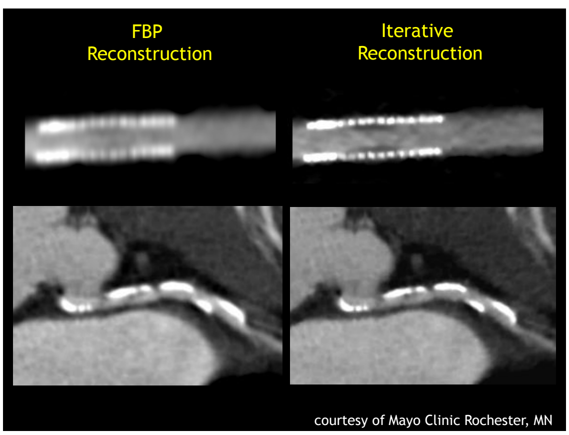
Model-based recons -s

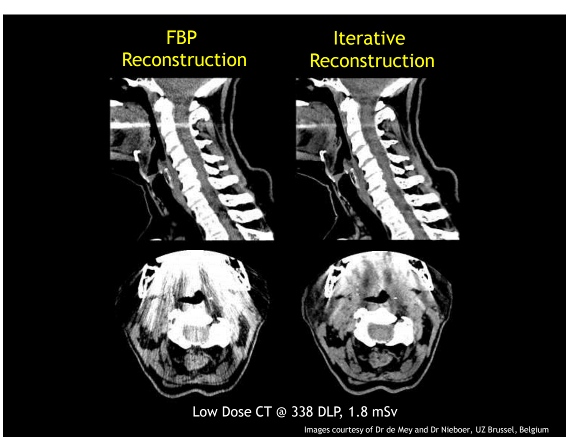
- Speed
- Increased vendor-dependence
- Unconventional image appearance
- Limited utility of prior quality m
- Need for nuanced implementati
effective improvement in patier

ASiR (GE)
Veo (GE)
IRIS (Siemens)
SAFIRE (Siemens)
AIDR (Toshiba)
iDose (Philips)
…




FBP
Reconstruction
Iterative
Reconstruction
courtesy of University of Erlangen, Germany

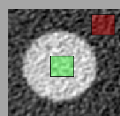

FBP
Reconstruction
Iterative
Reconstruction
courtesy of Mayo Clinic Rochester, MN


FBP
Reconstruction
Iterative
Reconstruction
Low Dose CT @ 338 DLP, 1.8 mSv
Images courtesy of Dr de Mey and Dr Nieboer, UZ Brussel, Belgium

Qualimetrics 1.0: CNR

- 1st order approximation of image quality
- Related to detectability for constant resolution and noise texture (Rose, 1948)
- Task-generic

$$CNR = \frac{Q_L - Q_B}{s_B}$$



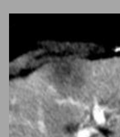
Parameters that affect IQ

1. Contrast
2. Lesion size
3. Lesion shape
4. Lesion edge profile
5. Resolution
6. Viewing distance
7. Display
8. Noise magnitude
9. Noise texture
10. Operator noise

Feature of interest

Image details

Distractors



Parameters that are measured by CNR

1. Contrast
2. Lesion size
3. Lesion shape
4. Lesion edge profile
5. Resolution
6. Viewing distance
7. Display
8. Noise magnitude
9. Noise texture
10. Operator noise

Feature of interest

Image details

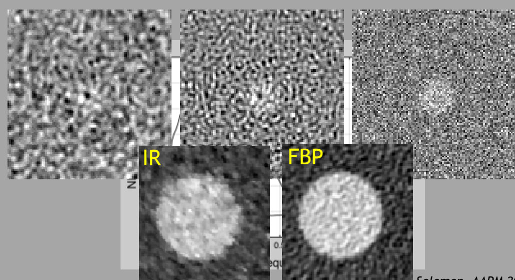
Distractors

1. Contrast

?

8. Noise magnitude

Why CNR is not enough: Noise texture

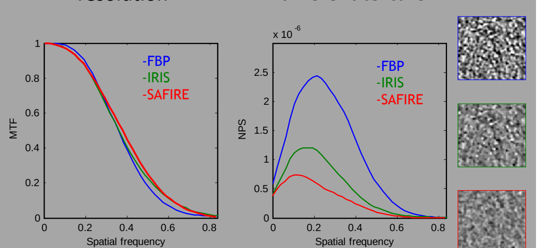


Solomon, AAPM 2012

Resolution and noise, eg 1

Comparable resolution

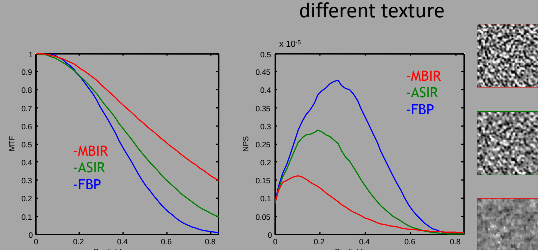
Lower noise but different texture



Resolution and noise, eg 2

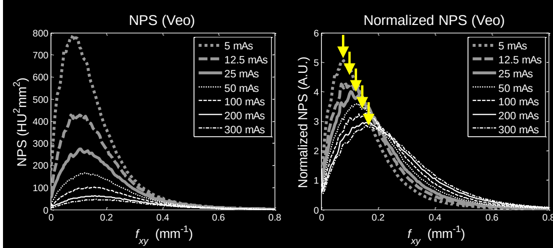
Higher resolution

Lower noise but different texture



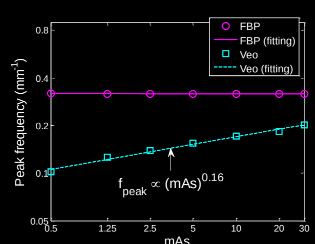
NPS vs dose

Nonlinearity



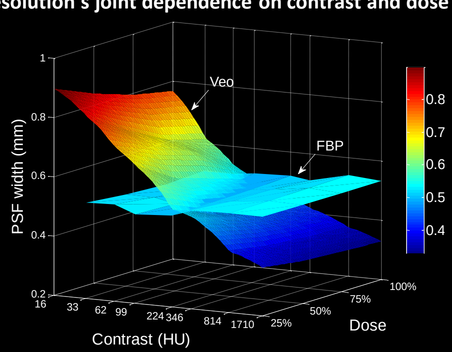
Li, Tang, and Chen, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance," *Med. Phys.* (2014)

NPS peak frequency vs dose

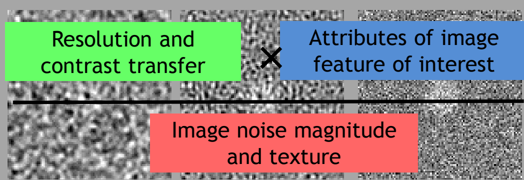


Li, Tang, and Chen, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance," *Med. Phys.* (2014)

Resolution's joint dependence on contrast and dose



Detectability index



$$\left(d'_{NPWE}\right)^2 = \frac{\left[\iint MTF^2(u,v)W^2_{Task}(u,v)E^2(u,v)dudv\right]^2}{\iint MTF^2(u,v)W^2_{Task}(u,v)NPS(u,v)E^4(u,v) + MTF^2(u,v)W^2_{Task}(u,v)N_i\,dudv}$$

Richard, and E. Samei, Quantitative breast tomosynthesis: from detectability to estimability. Med Phys, 37(12), 6157-65 (2010).
Chen et al., Relevance of MTF and NPS in quantitative CT: towards developing a predictable model of quantitative... SPIE2012

Task-based quality index

Fisher-Hotelling observer (FH)

$$\left(d'_{FH}\right)^2 = \iint \frac{MTF^2(u,v)W^2_{Task}(u,v)}{NPS(u,v)}dudv$$

Non-prewhitening observer (NPW)

$$\left(d'_{NPW}\right)^2 = \frac{\left[\iint MTF^2(u,v)W^2_{Task}(u,v)dudv\right]^2}{\iint MTF^2(u,v)W^2_{Task}(u,v)NPS(u,v)dudv}$$

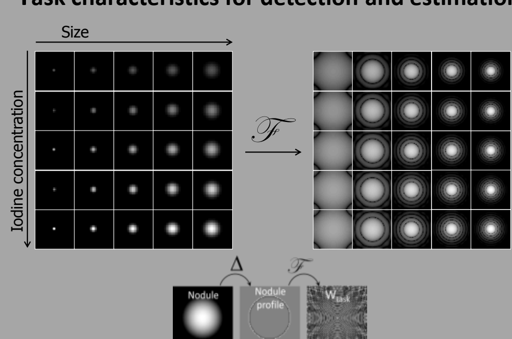
NPW observer with eye filter (NPWE)

$$\left(d'_{NPWE}\right)^2 = \frac{\left[\iint MTF^2(u,v)W^2_{Task}(u,v)E^2(u,v)dudv\right]^2}{\iint MTF^2(u,v)W^2_{Task}(u,v)NPS(u,v)E^4(u,v) + MTF^2(u,v)W^2_{Task}(u,v)N_i\,dudv}$$

Task function:

$C(r) = C_{peak}\left(1 - \left(\frac{r}{R}\right)^2\right)^n$

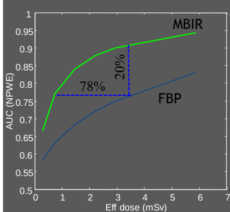
Task characteristics for detection and estimation



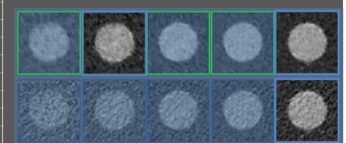
Chen, SPIE 2013

GE MBIR Dose Reduction Potential

Large feature detection task



ACR Acrylic insert

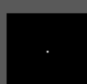


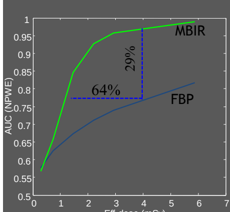
0.2 mSv → 3.7 mSv

Richard, Li, Samei, SPIE 2011

GE MBIR Dose Reduction Potential

Small feature detection task





ACR 0.5 lp/mm bar pattern

0.2 mSv → 3.7 mSv

Richard, Li, Samei, SPIE 2011

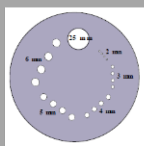
Christianson, AAPM 2012

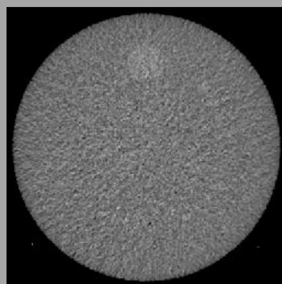
Duke-UMD-NIST study

Parameter	GE Discovery CT 750 HD	Siemens Flash	Philips iCT
kVp	120	120	120
Rotation time	0.5	0.5	0.5
SFOV	50	50	50
DFOV	25	25	25
Recon Algorithm	FBP Standard / $ASIR_{50}$	B31f / I30f Safire 3	B / iDose5
Recon Mode	Helical	Helical	Helical
Collimation	0.625	0.6	0.625
Pitch	0.984	1	0.93
Slice Thickness	1.25	1	1

Dose levels: 20, 12, 7.2, 4.3, 1.6, 0.9 mGy
For anonymity will be referred to as vendor A, B, and C

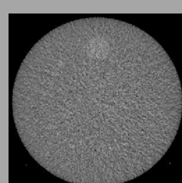
Observer study design





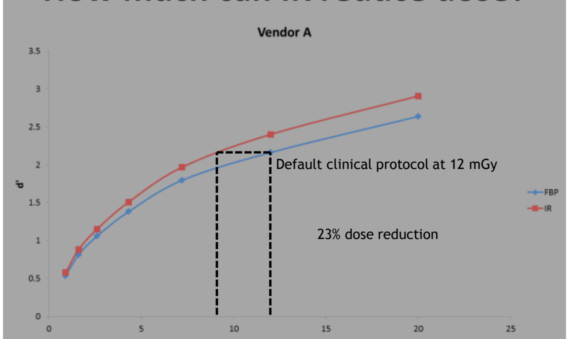
Observer study design

3 scanner models
3 dose levels
2 reconstruction algorithms
10 slices
x <u>5 repeated exams</u>
Total of 900 images

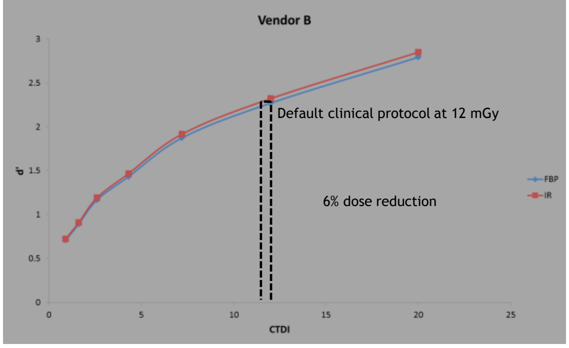


12 expert observers from two institutions

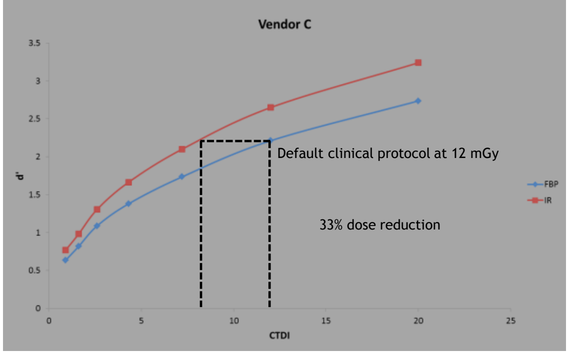
How much can IR reduce dose?



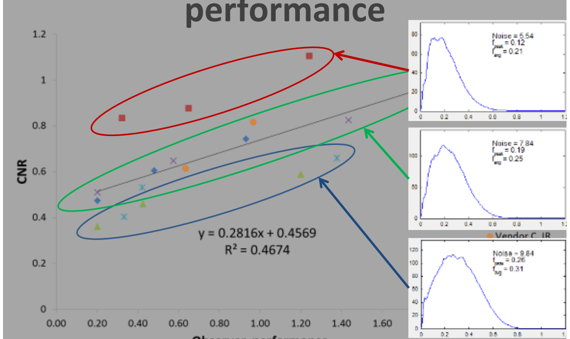
How much can IR reduce dose?



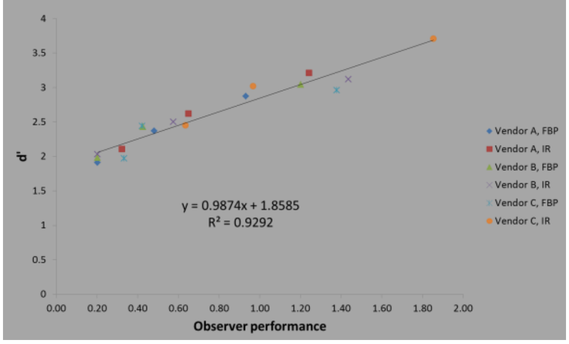
How much can IR reduce dose?



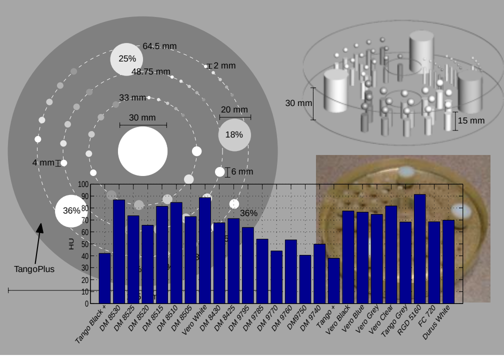
CNR vs observer performance



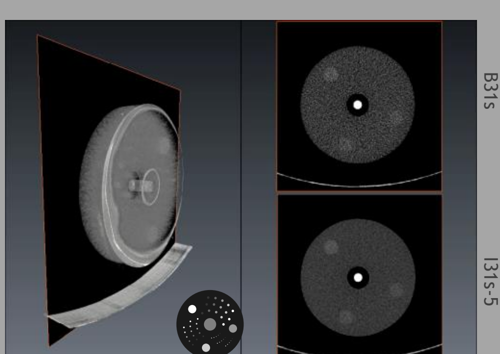
d’ vs observer performance



Our contrast detail phantom



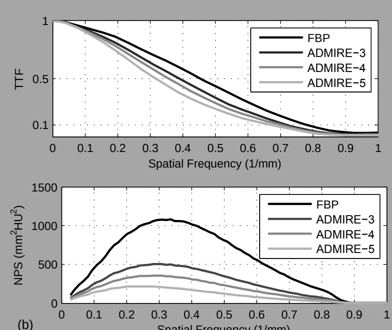
CT images of the low-contrast phantom



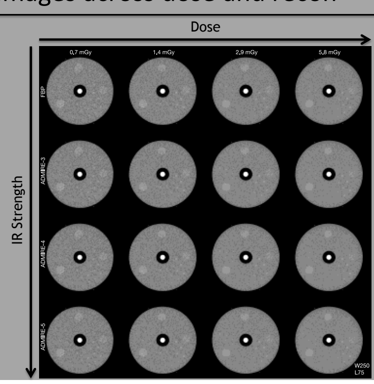
Acquired CT data

- Siemens SOMATOM Force
- 4 doses (0.7, 1.4, 2.9, 5.8 mGy)
- 2 slice thicknesses (0.6, 5 mm)
- 4 Recons (FBP, ADMIRE 3-5)

TTF and NPS across recons

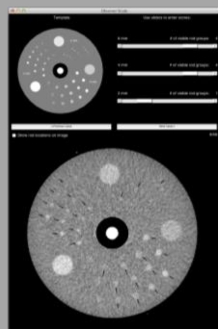


CT images across dose and recon

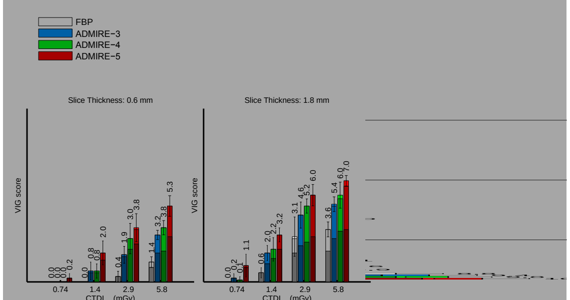


Insert Counting Experiment

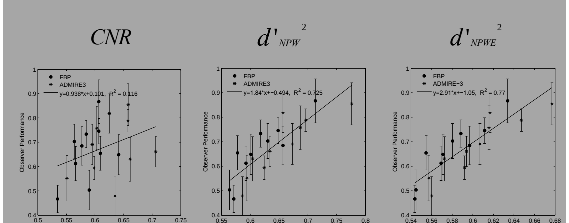
- Visible groups across:
  - Dose (0.74, 1.4, 2.9, 5.8 mGy)
  - Slice Thickness (0.6, 1.8, 5 mm)
  - Recon (FBP, ADMIRE 3-5)



Total number of discernable objects

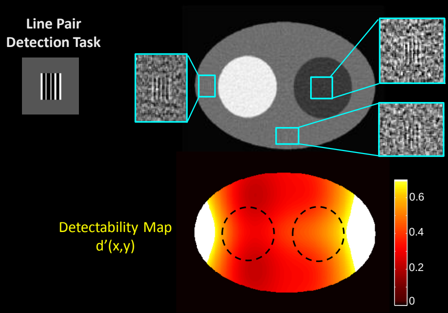


IQ metrics vs human performance



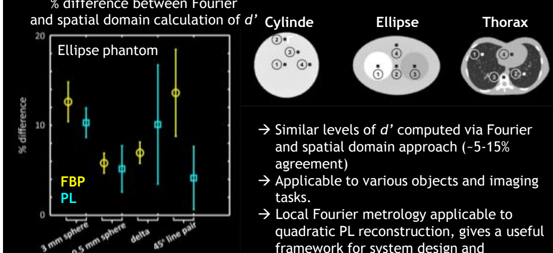
Task-Based Detectability

Extended to quadratic PL image reconstruction



G. Gang et al. Med Phys 41 (2014)

Justification of Assumptions: Local Stationarity and Linearity



→ Similar levels of *d'* computed via Fourier and spatial domain approach (~5-15% agreement)
→ Applicable to various objects and imaging tasks.
→ Local Fourier metrology applicable to quadratic PL reconstruction, gives a useful framework for system design and optimization.

G. Gang et al. Med Phys 41 (2014)

Estimability index (e'): prediction of the quantification precision capturing the interaction between the imaging system, the segmentation software, and the lesion

$$e'^2 = \frac{\left[\iiint TTF^2(u,v,w;C,N)\cdot\left|W_{task}(u,v,w)\right|^2 dudvdw\right]^2}{\iiint \left[NPS(u,v,w;N)+N_I(u,v,w)\right]\cdot\left|W_{task}(u,v,w)\right|^2 dudvdw}$$

Noise

3D Noise power spectrum (NPS)
Texture and magnitude of the noise

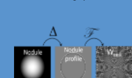
Internal noise (N_I)
Inconsistency of the quantification software due to placement of random seeds

Resolution

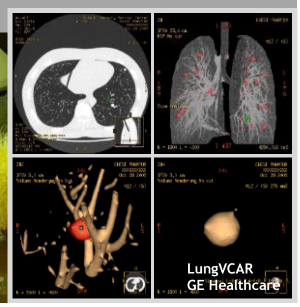
3D Task transfer function (TTF)
System resolution with respect to the contrast of the object and image noise

Tumor characteristics

3D Task function (W_{task})
Size, shape, and contrast of the nodule being quantified

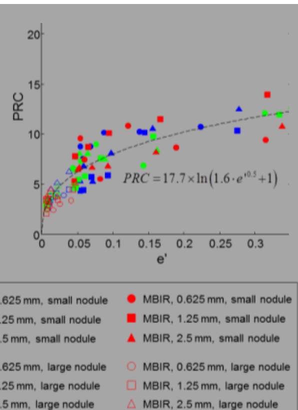


Empirical precision measurement



Predicted precision matches empirical precision!

$$PRC_j = 1.96\sqrt{2\sigma_{Wj}^2} / V_{true}$$
$$\approx 2.77\hat{\sigma}_{Wj} / V_{true}$$
$$= 2.77\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{K}\frac{(V_{ijk}-\bar{V}_{ij})^2}{n(K-1)}} / V_{true}$$

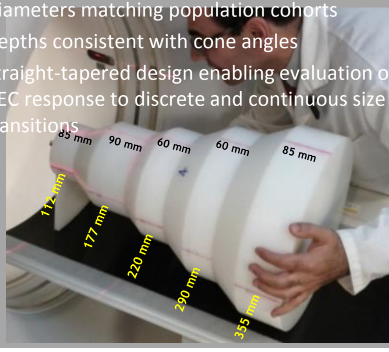


Outline

1. Quality Characterization
2. Quality assessment
3. Quality implementation

Task-based assessment metrology
Mercury Phantom 3.0

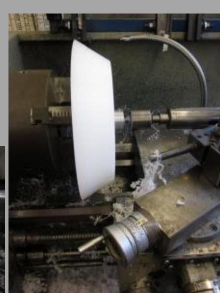
- Diameters matching population cohorts
- Depths consistent with cone angles
- Straight-tapered design enabling evaluation of AEC response to discrete and continuous size transitions



55

Design: Base material

- Polyethylene
  - 80 HU @ 120 KVp
  - Near patient equivalent
  - Affordable
  - Easy to machine



56

Design: Size
Pediatric representation percentages

MP 3.0 section	Water size equivalent	Abdomen		Chest		Head	
		Age	Percentile	Age	Percentile	Age	Percentile
120 mm	112 mm	0	12	0	50	0	5
		7	5	5.5	5		
185 mm	177 mm	6	50	10	50	3	95
		15	5	16	5	12	50
230 mm	220 mm	3	95	8	95	-	-
		12	50	16	50		
		21	5				
300 mm	290 mm	12	95	19	95	-	-
		21	50				
370 mm	355 mm	20	95	-	-	-	-

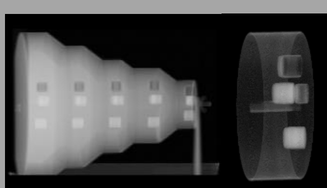
57

Design: Size
Adult representation percentages

MP 3.0 section	Water size equivalent	Abdomen		Chest		Head	
		M	F	M	F	M	F
120 mm	112 mm	-	-	-	-	-	-
185 mm	177 mm	-	-	-	-	25	75
230 mm	220 mm	0.4	9	0.06	1.4	-	-
300 mm	290 mm	27.1	61	14	48	-	-
370 mm	355 mm	80	90.3	60	87	-	-

58

Design: Resolution, HU, noise

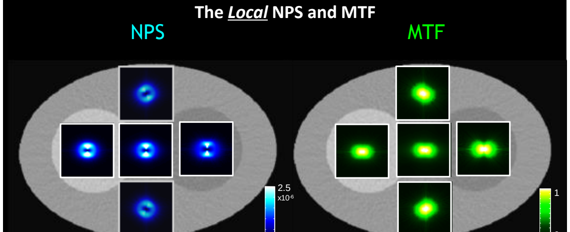


- Representation of abnormality-relevant HUs
- Sizes large enough for resolution sampling
- Maximum margin for individual assessment
- Iso-radius resolution properties
- Matching uniform section for noise assessment

59

Non-Stationary Noise and Resolution

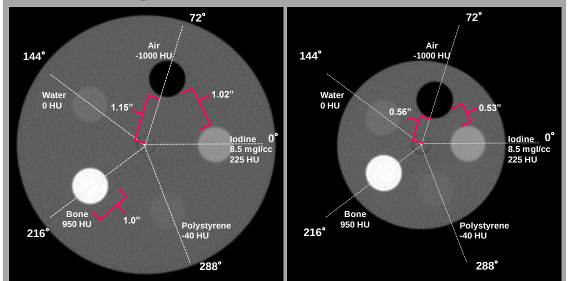
The *Local* NPS and MTF



Noise and resolution model for Penalized Likelihood (PL) model-based reconstruction.*
Predictive framework for NPS, MTF, and detectability index (*d'*) enables task-based design and optimization of new systems using iterative reconstruction.

***Fessler et al. IEEE-TIP (1996)**
G. Gang et al. Med Phys 41 (2014)

Design: Resolution, HU, noise

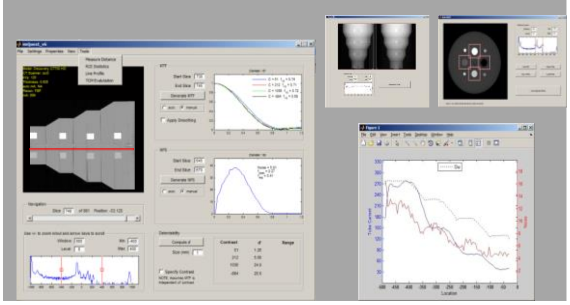


Sections 2-5 Smallest Section 1

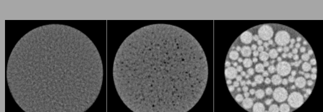
imQuest

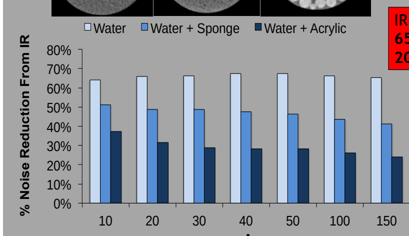
(image quality evaluation software)

HU, Contrast, Noise, CNR, MTF, NPS, and d' per patient size, mA modulation profile



Noise texture effect





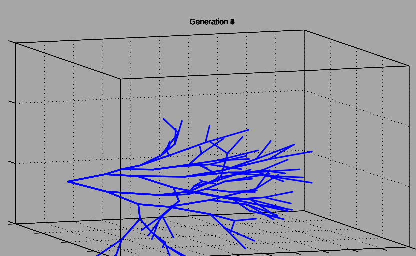
IR noise reduction:
65% in uniform bkgd
20% in textured bkgd

Solomon, SPIE 2012

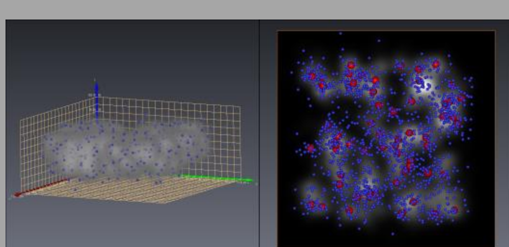
Mercury phantom 3.0

Added contrast detail and texture

Textured lung phantom

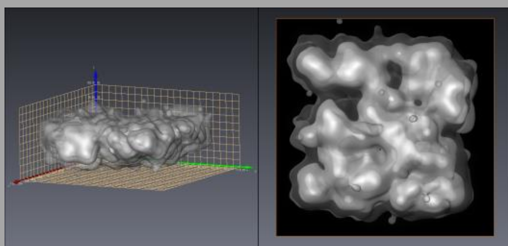


Textured soft-tissue phantom: clustered lumpy background*



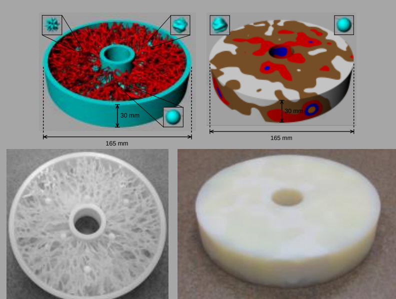
*Bochud, F., Abbey, C., & Eckstein, M. (1999). Statistical texture synthesis of mammographic images with super-blob lumpy backgrounds. Optics express, 4(1), 33-42. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19396254

Textured soft-tissue phantom: clustered lumpy background*



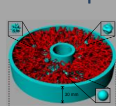
*Bochud, F., Abbey, C., & Eckstein, M. (1999). Statistical texture synthesis of mammographic images with super-blob lumpy backgrounds. Optics express, 4(1), 33-42. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19396254

Anatomically informed heterogeneity phantoms



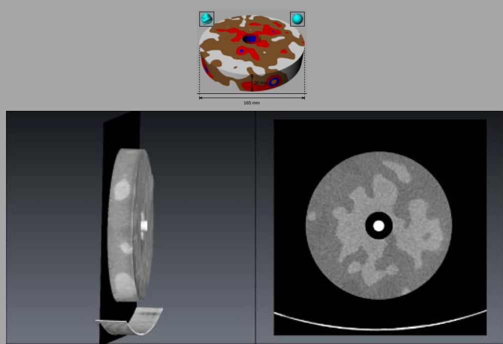
68

Lung texture phantom



69

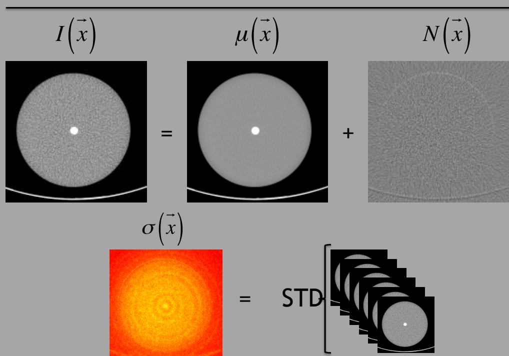
Soft-tissue texture phantom



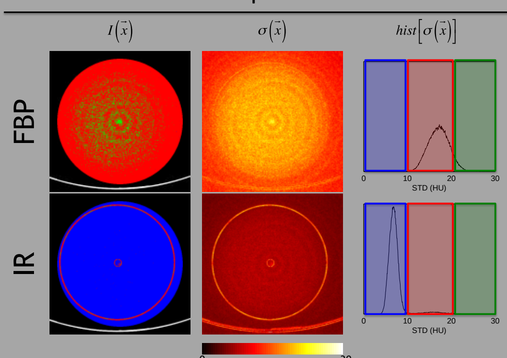
70

How was the data analyzed?

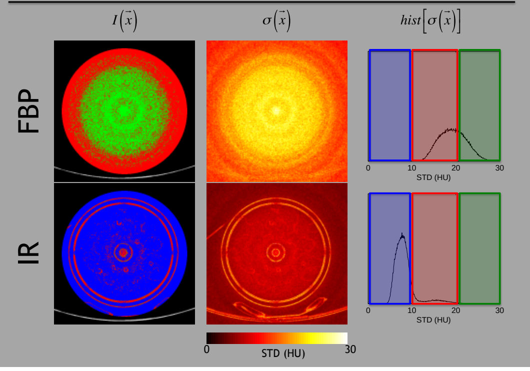
$\vec{x} = [x, y, z]$



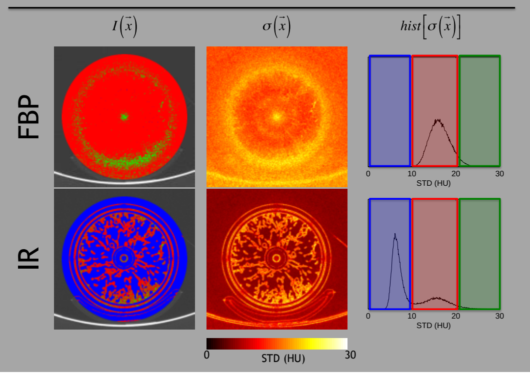
Noise in the uniform phantom



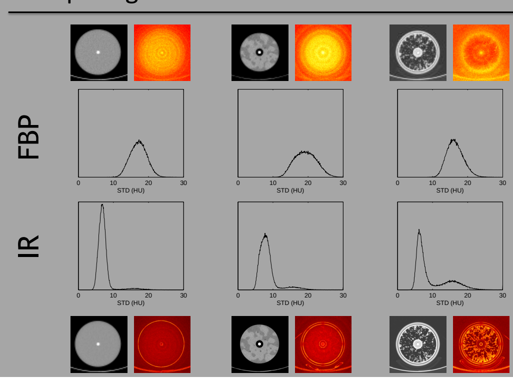
Noise in the soft-tissue phantom



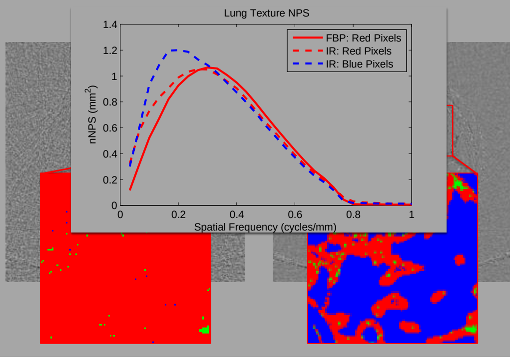
Noise in the lung phantom



Comparing noise across textures



What about noise texture? $I(\vec{x}) = \mu(\vec{x}) + \boxed{N(\vec{x})}$



Outline

1. Quality Characterization
2. Quality assessment
3. Quality implementation

Components of quality assurance

System performance assessment
Quality by inference

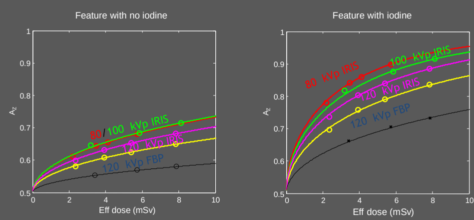
Prospective protocol definition
Quality by prescription

Retrospective performance assessment
Quality by outcome

kV IR optimization

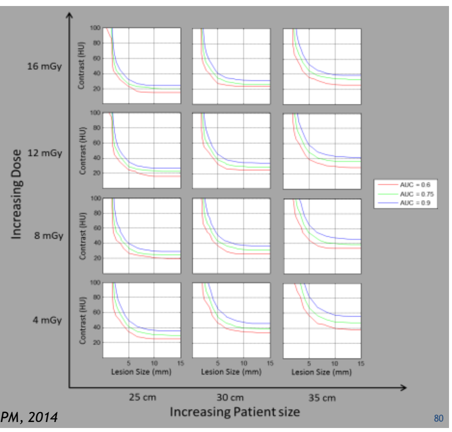
ACR phantom

Task	Optimal technique	% dose reduction (wrt 120 kVp FBP)
No Iodine	80/100 kVp with IRIS	36%
With Iodine	80 kVp with IRIS	40%



Samei, Richard, Med Phys, in press, 2014

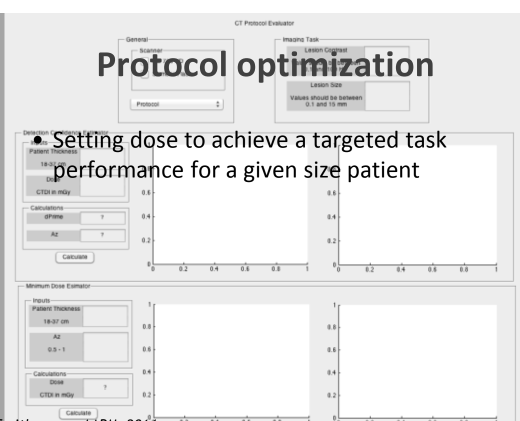
Detectability trends with dose/size



Smitherman, AAPM, 2014

80

Protocol optimization

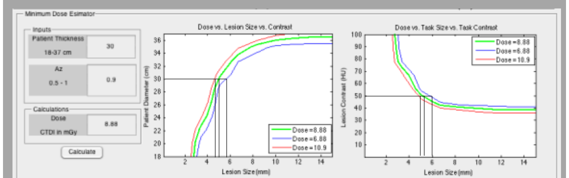


- Setting dose to achieve a targeted task performance for a given size patient

Smitherman, AAPM, 2014

Protocol optimization

- Setting dose to achieve a targeted task performance for a given size patient

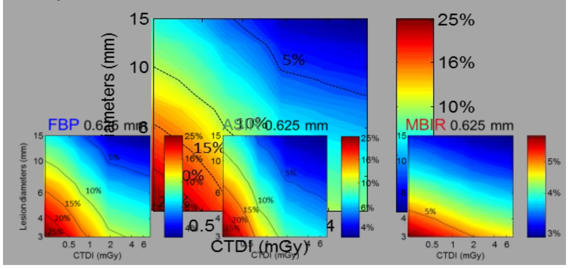


Smitherman, AAPM, 2014

Quality-dose dependency

Quantitative volumetry via CT

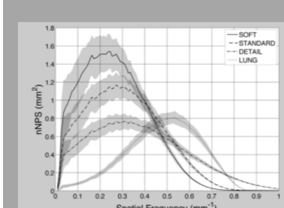
PRC: Relative difference between any two repeated quantifications of a nodule with 95% confidence

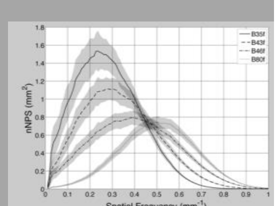


Noise texture vs kernel

GE

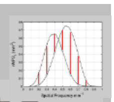
Siemens

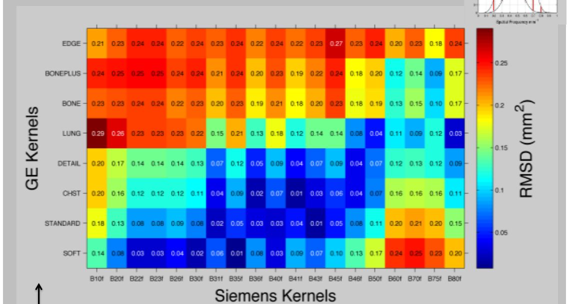




Solomon, Samei, Med Phys, 2012

Texture similarity

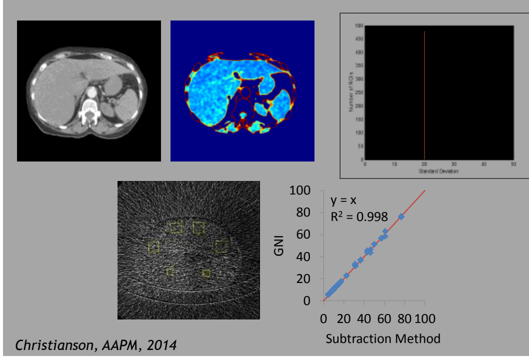




Sharpness

Solomon, Samei, Med Phys, 2012

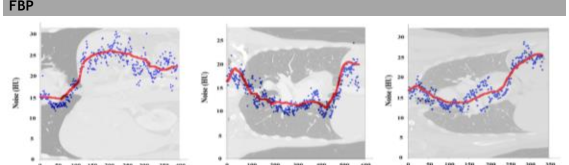
CT image quality monitoring



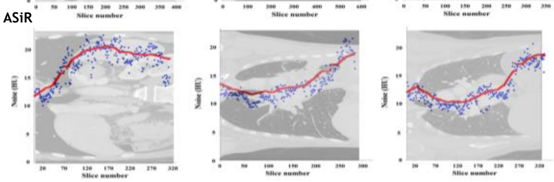
Christianson, AAPM, 2014

Noise per slice

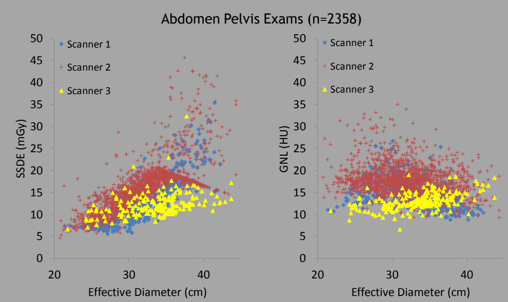
FBP



ASiR

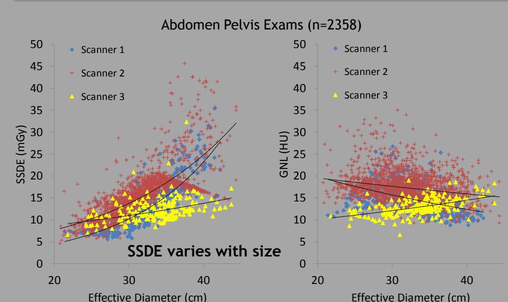


Trends in dose and noise



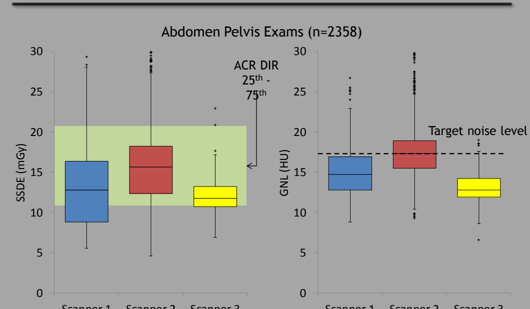
Christianson, AAPM, 2014

Trends in dose and noise



Christianson, AAPM, 2014

Variability in dose and noise



Christianson, AAPM, 2014

Conclusions

- New technologies necessitate an upgrade to performance metrology towards higher degrees of clinical relevance:
  - Physical surrogates of clinical performance
  - “Taskful” metrology and dependencies
  - Incorporation of texture into image quality estimation
  - Extension of quality metrology to quality monitoring and quality analytics