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Multi-energy CT: Data and image analysis methods

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Outline

- Analysis methods for non-material specific imaging
  - Optimal weighting
  - Virtual monochromatic
- Analysis methods for material specific imaging
  - Basis material and PE-Compton decomposition, K-edge
  - Image space vs. projection space
  - Dimensionality analysis and noise considerations
  - Three material decomposition
  - Material classification

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Multi-energy CT

- Non-material specific imaging
  - Virtual monochromatic
  - Optimal weighting

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Reduce artifacts and improve quantitative accuracy
Improve SNR and dose efficiency

- Material specific imaging
  - Basis material decomposition
  - PE-Compton decomposition
  - K-edge imaging (photon-counting multi-energy)

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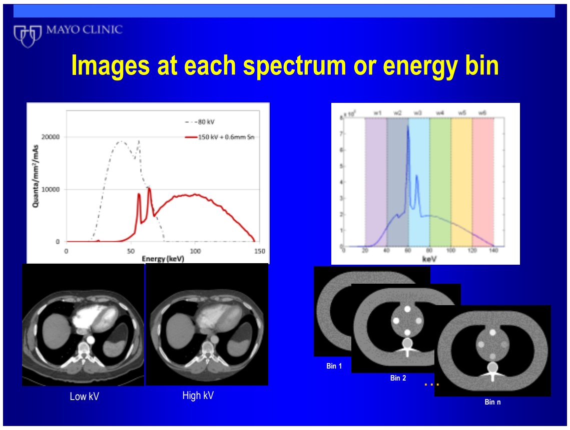
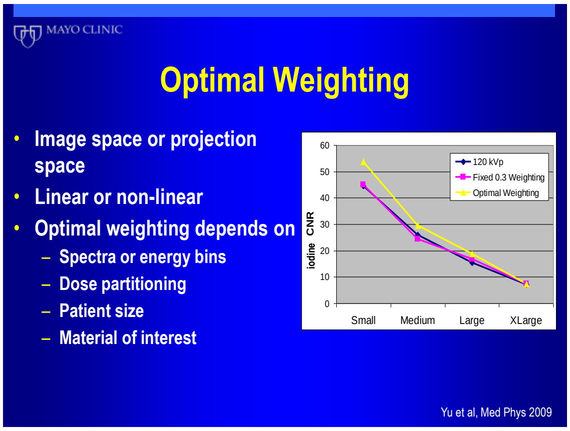
Expand CT clinical applications
- Material quantification (e.g., iodine, bone, high-Z contrast agent)
- Material classification (e.g., bone/iodine, uric acid/non-uric acid)

Non-material specific imaging



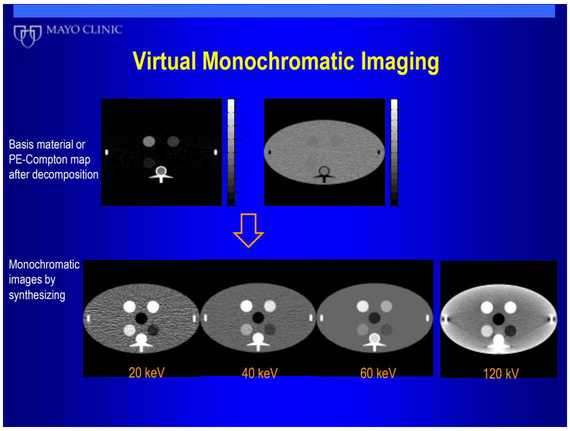
Images at each spectrum or energy bin



Optimal Weighting

- Image space or projection space
- Linear or non-linear
- Optimal weighting depends on
  - Spectra or energy bins
  - Dose partitioning
  - Patient size
  - Material of interest

Yu et al, Med Phys 2009



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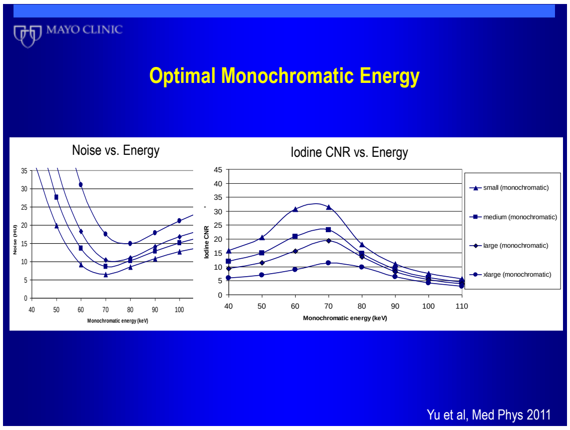
Virtual Monochromatic Imaging

Basis material or PE-Compton map after decomposition

Monochromatic images by synthesizing



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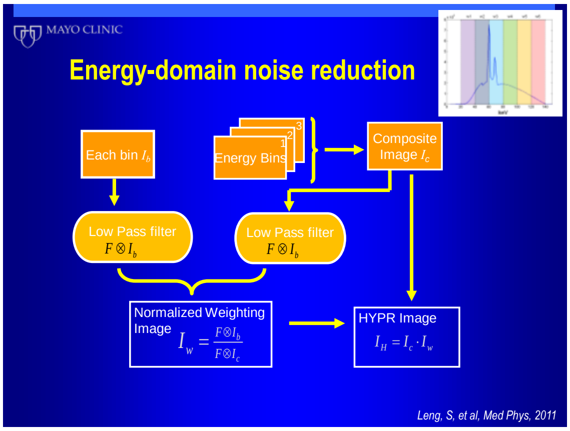
Optimal Monochromatic Energy

Yu et al, Med Phys 2011



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Energy-domain noise reduction

Each bin I_b

Energy Bins

Composite Image I_c

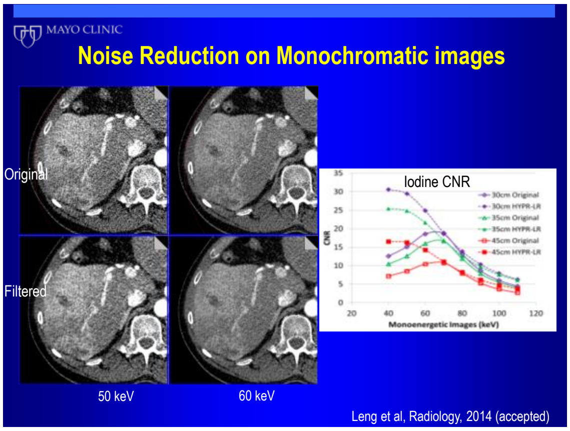
Low Pass filter $F \otimes I_b$

Low Pass filter $F \otimes I_b$

Normalized Weighting Image $I_w = \frac{F \otimes I_b}{F \otimes I_c}$

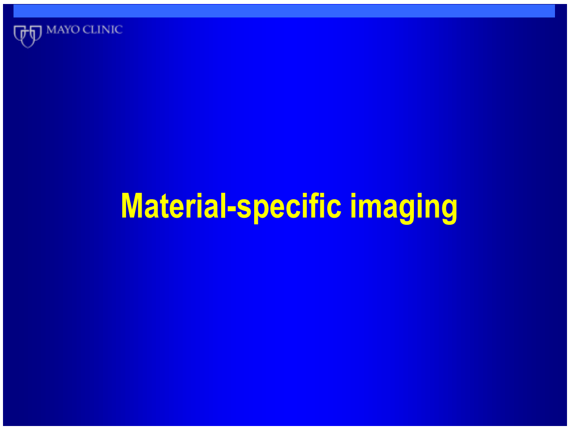
HYPR Image $I_H = I_c \cdot I_w$

Leng, S, et al, Med Phys, 2011

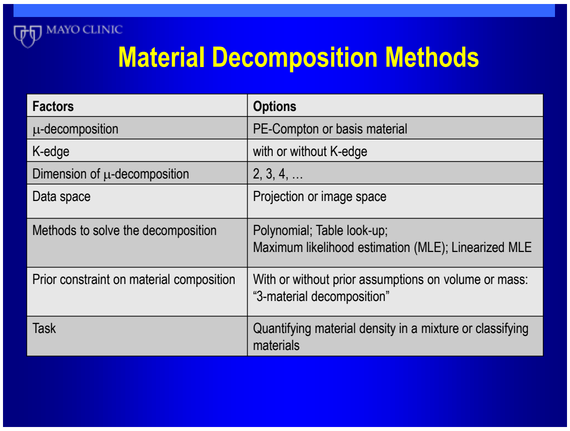


Noise Reduction on Monochromatic images

Leng et al, Radiology, 2014 (accepted)

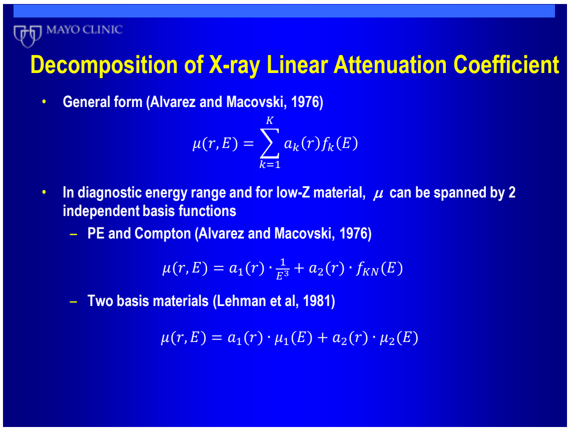


Material-specific imaging



Material Decomposition Methods

Factors	Options
μ-decomposition	PE-Compton or basis material
K-edge	with or without K-edge
Dimension of μ-decomposition	2, 3, 4, …
Data space	Projection or image space
Methods to solve the decomposition	Polynomial; Table look-up; Maximum likelihood estimation (MLE); Linearized MLE
Prior constraint on material composition	With or without prior assumptions on volume or mass: "3-material decomposition"
Task	Quantifying material density in a mixture or classifying materials



Decomposition of X-ray Linear Attenuation Coefficient

- General form (Alvarez and Macovski, 1976)

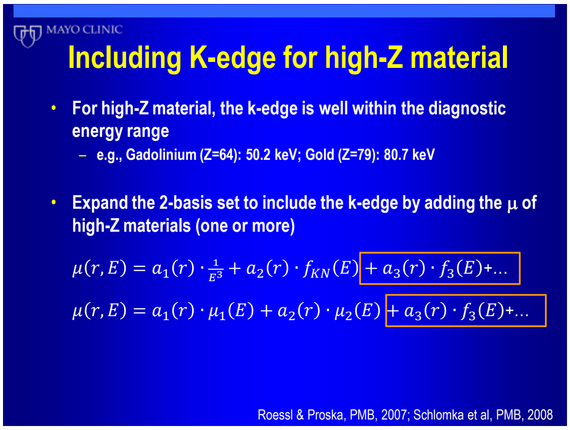
$$\mu(r,E) = \sum_{k=1}^{K} a_k(r) f_k(E)$$

- In diagnostic energy range and for low-Z material, μ can be spanned by 2 independent basis functions
  - PE and Compton (Alvarez and Macovski, 1976)

$$\mu(r,E) = a_1(r) \cdot \frac{1}{E^3} + a_2(r) \cdot f_{KN}(E)$$

  - Two basis materials (Lehman et al, 1981)

$$\mu(r,E) = a_1(r) \cdot \mu_1(E) + a_2(r) \cdot \mu_2(E)$$



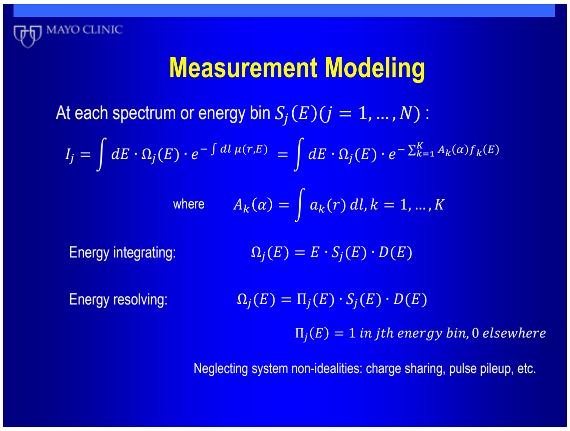
Including K-edge for high-Z material

- For high-Z material, the k-edge is well within the diagnostic energy range
  - e.g., Gadolinium (Z=64): 50.2 keV; Gold (Z=79): 80.7 keV
- Expand the 2-basis set to include the k-edge by adding the μ of high-Z materials (one or more)

$$\mu(r,E) = a_1(r) \cdot \frac{1}{E^3} + a_2(r) \cdot f_{KN}(E) \boxed{+ a_3(r) \cdot f_3(E) + \ldots}$$

$$\mu(r,E) = a_1(r) \cdot \mu_1(E) + a_2(r) \cdot \mu_2(E) \boxed{+ a_3(r) \cdot f_3(E) + \ldots}$$

Roessl & Proska, PMB, 2007; Schlomka et al, PMB, 2008



Measurement Modeling

At each spectrum or energy bin $S_j(E) (j = 1, \ldots, N)$:

$$I_j = \int dE \cdot \Omega_j(E) \cdot e^{-\int dl\, \mu(r,E)} = \int dE \cdot \Omega_j(E) \cdot e^{-\sum_{k=1}^{K} A_k(\alpha) f_k(E)}$$

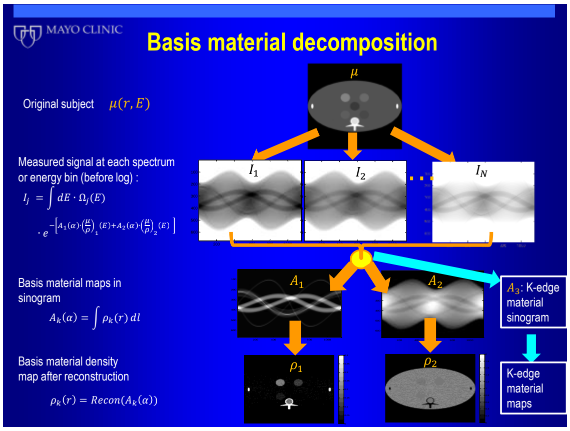
where $A_k(\alpha) = \int a_k(r)\, dl, k = 1, \ldots, K$

Energy integrating: $\Omega_j(E) = E \cdot S_j(E) \cdot D(E)$

Energy resolving: $\Omega_j(E) = \Pi_j(E) \cdot S_j(E) \cdot D(E)$

$\Pi_j(E) = 1 \textit{ in jth energy bin, } 0 \textit{ elsewhere}$

Neglecting system non-idealities: charge sharing, pulse pileup, etc.



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Basis material decomposition

Original subject $\mu(r, E)$

Measured signal at each spectrum or energy bin (before log) :

$$I_j = \int dE \cdot \Omega_j(E) \cdot e^{-\left[A_1(\alpha)\cdot\left(\frac{\mu}{\rho}\right)_1(E)+A_2(\alpha)\cdot\left(\frac{\mu}{\rho}\right)_2(E)\right]}$$

Basis material maps in sinogram

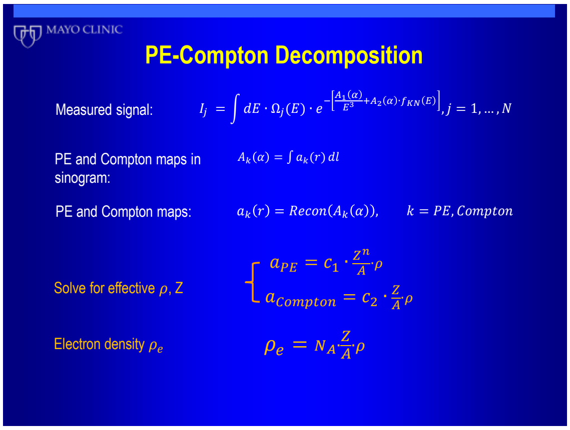
$$A_k(\alpha) = \int \rho_k(r)\, dl$$

Basis material density map after reconstruction

$$\rho_k(r) = Recon(A_k(\alpha))$$

A_3: K-edge material sinogram

K-edge material maps



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PE-Compton Decomposition

Measured signal: $I_j = \int dE \cdot \Omega_j(E) \cdot e^{-\left[\frac{A_1(\alpha)}{E^3}+A_2(\alpha)\cdot f_{KN}(E)\right]}, j = 1, \ldots, N$

PE and Compton maps in sinogram: $A_k(\alpha) = \int a_k(r)\, dl$

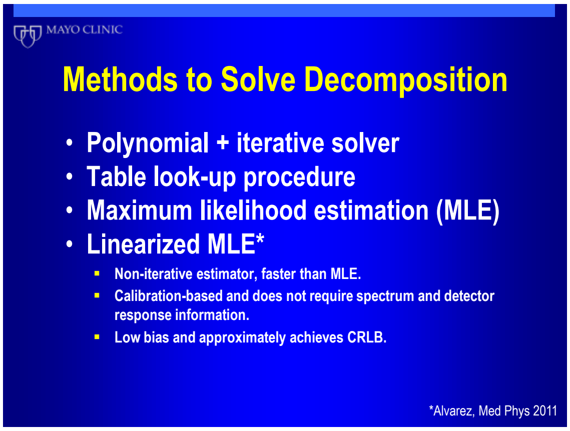
PE and Compton maps: $a_k(r) = Recon(A_k(\alpha)), \quad k = PE, Compton$

Solve for effective ρ, Z

$$\begin{cases} a_{PE} = c_1 \cdot \frac{Z^n}{A} \cdot \rho \\ a_{Compton} = c_2 \cdot \frac{Z}{A} \cdot \rho \end{cases}$$

Electron density ρ_e

$$\rho_e = N_A \cdot \frac{Z}{A} \cdot \rho$$



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Methods to Solve Decomposition

- Polynomial + iterative solver
- Table look-up procedure
- Maximum likelihood estimation (MLE)
- Linearized MLE*
  - Non-iterative estimator, faster than MLE.
  - Calibration-based and does not require spectrum and detector response information.
  - Low bias and approximately achieves CRLB.

*Alvarez, Med Phys 2011

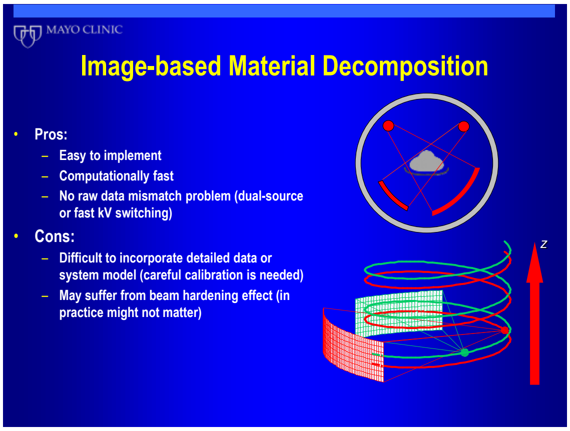
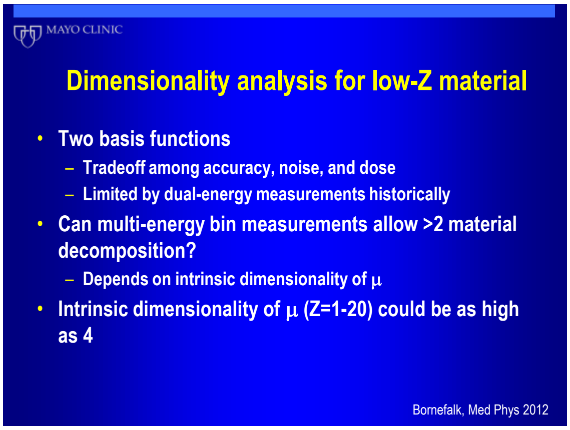


Image-based Material Decomposition

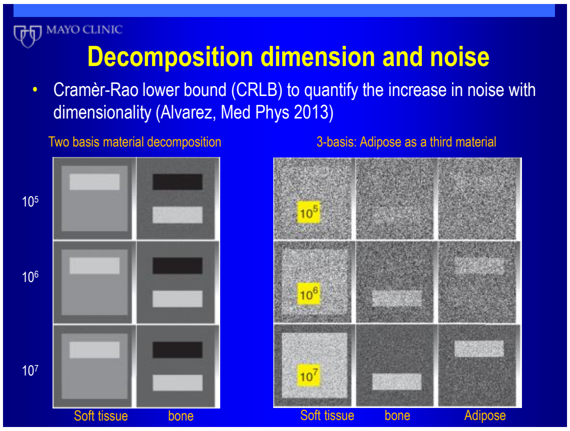
- Pros:
  - Easy to implement
  - Computationally fast
  - No raw data mismatch problem (dual-source or fast kV switching)
- Cons:
  - Difficult to incorporate detailed data or system model (careful calibration is needed)
  - May suffer from beam hardening effect (in practice might not matter)



Dimensionality analysis for low-Z material

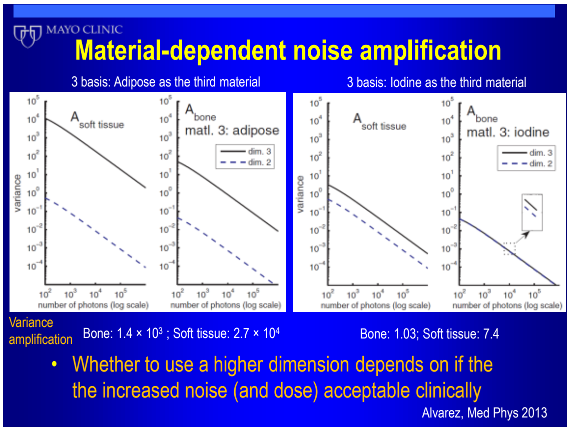
- Two basis functions
  - Tradeoff among accuracy, noise, and dose
  - Limited by dual-energy measurements historically
- Can multi-energy bin measurements allow >2 material decomposition?
  - Depends on intrinsic dimensionality of μ
- Intrinsic dimensionality of μ (Z=1-20) could be as high as 4

Bornefalk, Med Phys 2012



Decomposition dimension and noise

- Cramèr-Rao lower bound (CRLB) to quantify the increase in noise with dimensionality (Alvarez, Med Phys 2013)



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Material-dependent noise amplification

3 basis: Adipose as the third material

3 basis: Iodine as the third material

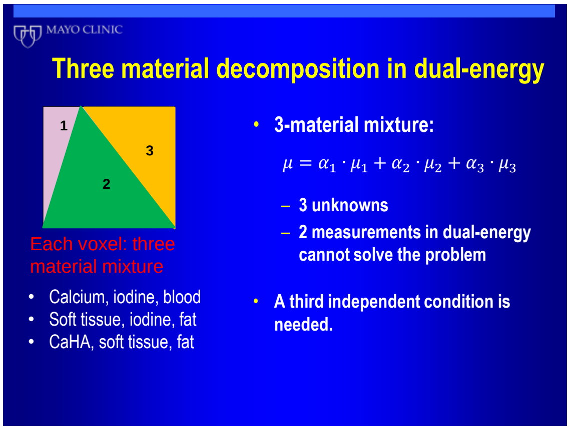
Variance amplification

Bone: 1.4×10^3 ; Soft tissue: 2.7×10^4

Bone: 1.03; Soft tissue: 7.4

- Whether to use a higher dimension depends on if the the increased noise (and dose) acceptable clinically

Alvarez, Med Phys 2013



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Three material decomposition in dual-energy

Each voxel: three material mixture

- Calcium, iodine, blood
- Soft tissue, iodine, fat
- CaHA, soft tissue, fat

- **3-material mixture:**

$$\mu = \alpha_1 \cdot \mu_1 + \alpha_2 \cdot \mu_2 + \alpha_3 \cdot \mu_3$$

  - **3 unknowns**
  - **2 measurements in dual-energy cannot solve the problem**
- **A third independent condition is needed.**

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Assumptions on 3-material mixture

- **First order approximation:**

$$\rho_w(\rho_1, \rho_2) = \rho_{w0} + \rho_1 \frac{\partial \rho_w}{\rho_1} + \rho_2 \frac{\partial \rho_w}{\rho_2}$$

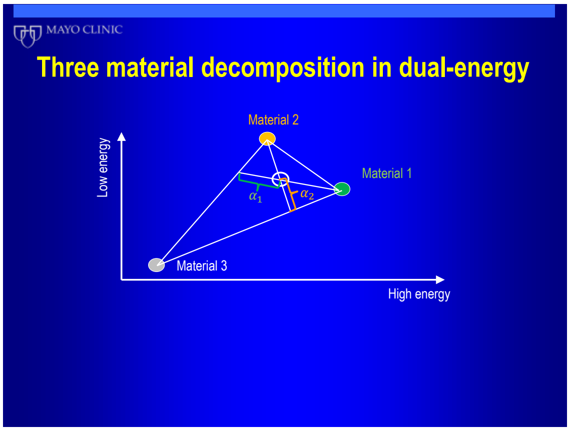
- **Volume conservation (incompressible)**

$$\alpha_1 + \alpha_2 + \alpha_3 = 1$$

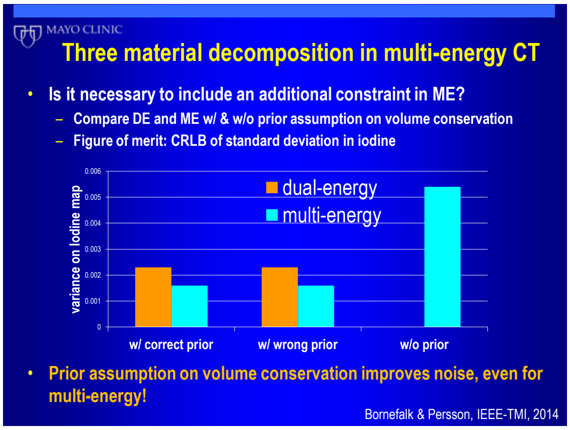
$\alpha_i = \frac{\rho_i}{\rho_{io}}$: volume fraction

- **Mass conservation (Need to calculate effective density at first)**

Kelcz et al, Med Phys 1978
Yu et al, SPIE 2009
Liu et al, Med Phys 2009



Three material decomposition in dual-energy

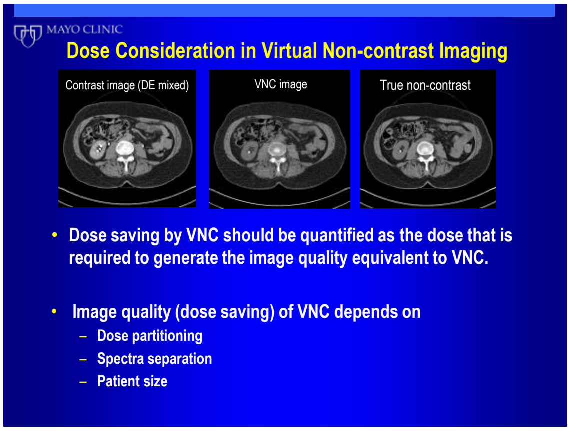


Three material decomposition in multi-energy CT

- Is it necessary to include an additional constraint in ME?
  - Compare DE and ME w/ & w/o prior assumption on volume conservation
  - Figure of merit: CRLB of standard deviation in iodine

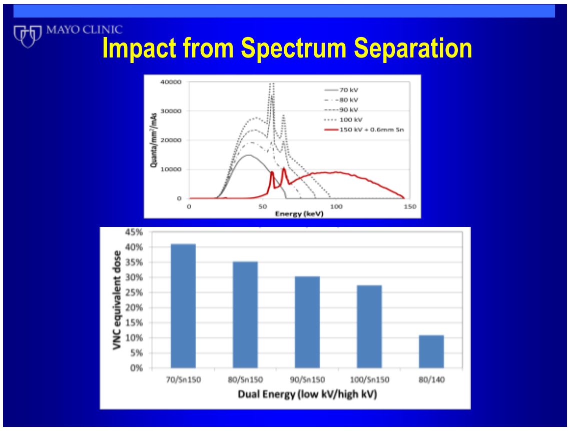
- Prior assumption on volume conservation improves noise, even for multi-energy!

Bornefalk & Persson, IEEE-TMI, 2014

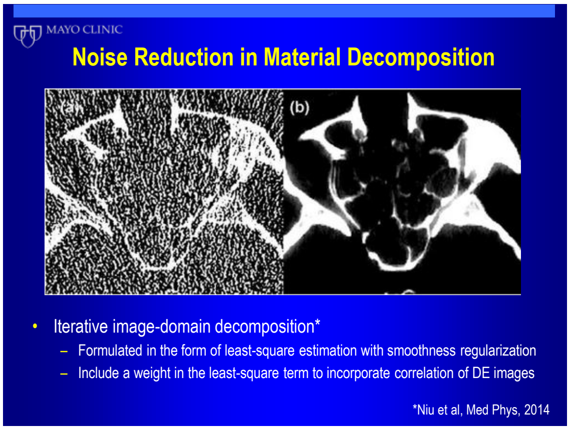


Dose Consideration in Virtual Non-contrast Imaging

- Dose saving by VNC should be quantified as the dose that is required to generate the image quality equivalent to VNC.
- Image quality (dose saving) of VNC depends on
  - Dose partitioning
  - Spectra separation
  - Patient size



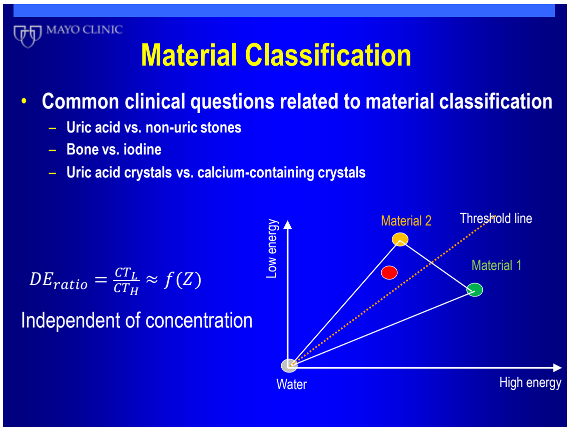
Impact from Spectrum Separation



Noise Reduction in Material Decomposition

- Iterative image-domain decomposition*
  - Formulated in the form of least-square estimation with smoothness regularization
  - Include a weight in the least-square term to incorporate correlation of DE images

*Niu et al, Med Phys, 2014

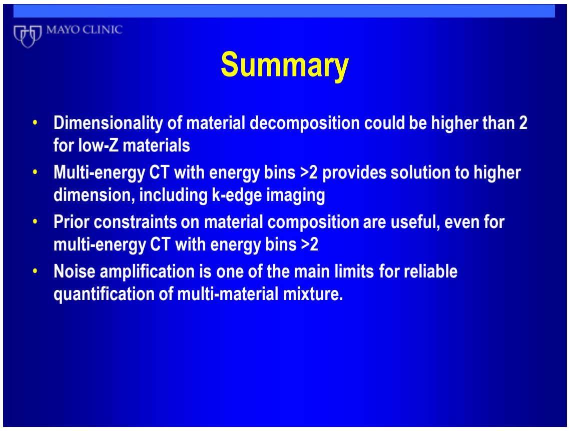


Material Classification

- **Common clinical questions related to material classification**
  - **Uric acid vs. non-uric stones**
  - **Bone vs. iodine**
  - **Uric acid crystals vs. calcium-containing crystals**

$$DE_{ratio} = \frac{CT_L}{CT_H} \approx f(Z)$$

Independent of concentration



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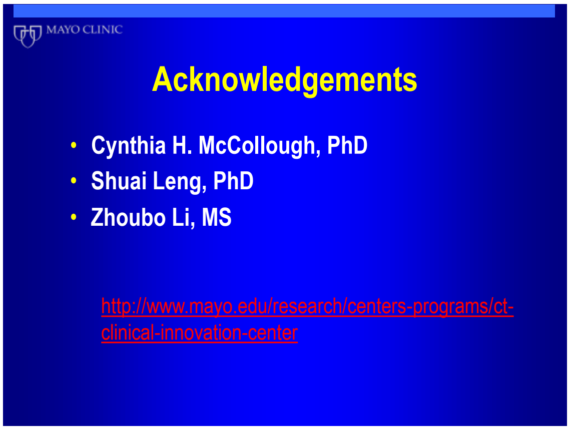
Summary

- Dimensionality of material decomposition could be higher than 2 for low-Z materials
- Multi-energy CT with energy bins >2 provides solution to higher dimension, including k-edge imaging
- Prior constraints on material composition are useful, even for multi-energy CT with energy bins >2
- Noise amplification is one of the main limits for reliable quantification of multi-material mixture.



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http://www.mayo.edu/research/centers-programs/ct-clinical-innovation-center