

Nonlinear regularized decomposition of spectral x-ray projection images

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SPECTRAL CT IMAGING

Conventional vs. Spectral = Grey level vs Color! \succ





- Average attenuation - Arbitrary units

- + Chemical components
- + Density (g.cm-3)
- + K-edge contrast imaging

[Cormode *et al.*, *Radiology*, 256 (3), 2010]

Sinogram



Tomographic Reconstruction





Sinogram

Photon Counting Detector Tomographic Reconstruction



object

Sinogram

Photon Counting Detector Tomographic Reconstruction



object

Sinogram

Photon Counting Detector



Tomographic Reconstruction



Sinogram



Tomographic Reconstruction



object

Sinogram



Spectral Tomographic Reconstruction

[Mendoca, et al., IEEE TMI, 2014] [Long and Fessler, IEEE TMI, 2014] [Zhang et al., IEEE TMI, 2014] [Barber, Fully 3D, 2015]

object



Sinogram

Material sinogram



Sinogram

Material sinogram



Sinogram

Material sinogram



Decomposition

[Alvarez *et al.*, PMB, 1976] [Brody *et al.*, Med. Phys, 1981] [Schlomka *et al.*, PMB, 2007] [Roessl et al., PMB, 2007]



> Why material decomposition of the sinogram?

- I. Embeds all the **nonlinearities** of spectral CT
- 2. Naturally **parallelizable** across the projection views
- 3. Applicable to both CT and interventional radiography

Sinogram



Decomposition

[Alvarez *et al.*, PMB, 1976] [Brody *et al.*, Med. Phys, 1981] [Schlomka *et al.*, PMB, 2007] [Roessl et al., PMB, 2007]

Material sinogram









> 2D projection images at a fixed view



> 2D projection images at a fixed view

> Notations

Photon numbers (no units) S =

Projected mass (in g.cm⁻²) $\mathbf{a} =$



> 2D projection images at a fixed view



Variational framework

- Nonlinear decomposition
- Regularized decomposition

$$C(\mathbf{a}) = \mathcal{D}(\mathbf{s}, \mathcal{F}(\mathbf{a})) + \alpha \mathcal{R}(\mathbf{a})$$

Gauss-Newton algorithm



- Gold standard
- Superlinear convergence rates





 \geq



Storage of the full Hessian is intractable!



- Storage of the full Hessian is intractable!
- Hessian is block diagonal with only PM² non zero entries

Forward model

$$s_i(\mathbf{u}) = \int_{\mathbb{R}} n_0(E) d_i(E) \exp\left(-\sum_{m=1}^M a_m(\mathbf{u})\tau_m(E)\right) \, \mathrm{d}E$$





Forward model

 n_0

 d_i



Forward model



Numerical Phantom

✤ 3-material Thorax Phantom

3D CT scan (a.u) [3D-IRCADb data set]



Materials

- Soft tissue
- Bone
- Gadolinium (Portal vein)

3D volumes (g.cm⁻³)



Projection (RTK) http://www.openrtk.org/



3D atlas (labels) [Kéchichian *et al.,* IEEE TIP, 2013]

2D image (g.cm⁻²)





frontal view

lateral view

A typical decomposition

$$C(\mathbf{a}) = D(\mathbf{s}, \mathcal{F}(\mathbf{a})) + \alpha \mathcal{R}(\mathbf{a})$$

Weighted least squares

 $\mathcal{D}(\mathbf{s}, \boldsymbol{\mathcal{F}}(\mathbf{a})) = \|\mathbf{s} - \boldsymbol{\mathcal{F}}(\mathbf{a})\|_{\mathbf{W}}^2$

Material-dependent regularization

$$\mathcal{R}(\mathbf{a}) = \|\Delta \mathbf{a}_{soft}\|_2^2 + \|\nabla \mathbf{a}_{bone}\|_2^2 + \|\nabla \mathbf{a}_{Gd}\|_1$$



20

10

 u_{bone}







A typical decomposition

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> Convergence of the algorithm



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> Influence of noise

Poisson noise

$$\tilde{s}_i = \mathcal{P}(\mu = s_i)$$



Decreasing s_i i.e. decreasing SNR

Influence of noise

Poisson noise

 $\tilde{s}_i = \mathcal{P}(\mu = s_i)$



Error vs noise



Decreasing s_i i.e. decreasing SNR

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Poisson noise

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Error vs noise



Decreasing s_i i.e. decreasing SNR

Influence of noise

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Error vs noise



- > Influence of the marker concentration
 - ✤ Concentration range: 0.01 to 1 g.cm⁻³



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CONCLUSION

Material decomposition

We proposed a GN algorithm

- Weighted least squares
- L₂/L₁ material dependent regularization
- > Thorax phantom with portal vein marked with gadolinium
 - Different number of counts
 - Different marker concentrations

Encouraging results

- ✤ Fast convergence
- Good reconstruction quality

- > Thanks to the spectral CT team
 - ✤ Juan FPJ ABASCAL
 - ✤ Tom HOHWEILLER
 - ✤ Jean-Michel LÉTANG
 - ✤ Cyril MORY
 - Françoise PEYRIN
 - Odran PIVOT
 - Simon RIT
 - Bruno SIXOU
 - ✤ Gloria VILCHES FREIXAS



THANK YOU FOR YOUR ATTENTION

- Convergence
 - Stopping criteria
 - \circ Step Length

$$\lambda^{(k)} = \arg \min \mathcal{C}(\mathbf{a}^{(k)} + \lambda \Delta \mathbf{a}^{(k)})$$

○ Cost function decrease

$$\frac{\mathcal{C}^{(k-1)}-\mathcal{C}^{(k)}}{\mathcal{C}^{(k-1)}}$$



> Choice of the regularization parameter



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