Beam Hardening Correction via Mass Attenuation Discretization

 \mathcal{T}^{in}

 au^{out}

 (μ, α)

Renliang Gu and Aleksandar Dogandžić {renliang, ald}@iastate.edu Department of Electrical and Computer Engineering

Background

According to the Lambert-Beer's law [Jenkins and White 1957], the fraction $d\mathcal{I}/\mathcal{I}$ of plane wave intensity lost in traversing an infinitesimal thickness $d\ell$ at Cartesian coordinates (x, y) is proportional to $d\ell$, so that

$$\frac{\mathrm{d}\mathcal{I}}{\mathcal{I}} = -\mu(\varepsilon)\alpha(x, y)\,\mathrm{d}\ell.$$

where

- $\blacktriangleright \mu(\varepsilon)$ is the mass attenuation coefficient of the material (in $\frac{\text{cm}^2}{\sigma}$), which depends only on the photon energy ε ,
- $\alpha(x, y)$ is the density map of the inspected object (in $\frac{g}{cm^3}$).

Therefore, a monochromatic X-ray signal at photon energy ε attenuates *exponentially* as it penetrates an object composed of a single material:

 $\mathcal{I}^{\mathsf{out}} = \mathcal{I}^{\mathsf{in}} \exp\left[-\mu(\varepsilon) \int_{\ell} \alpha(x, y) \,\mathrm{d}\ell\right].$

where \mathcal{I}^{out} and \mathcal{I}^{in} are the emergent and incident X-ray signal energies, respectively.

However, X-rays generated by vacuum tubes are not monochromatic. To describe the polychromatic X-ray source, assume that its incident intensity \mathcal{I}^{in} spreads along photon energy ε following the density $\iota(\varepsilon)$, i.e.,

$$\int \iota(\varepsilon) \,\mathrm{d}\varepsilon = \mathcal{I}^{\mathsf{in}}.\tag{1a}$$

Then, the noiseless measurement collected by an energy integral detector upon traversing a straight line $\ell = \ell(x, y)$ is

$$\mathcal{I}^{\mathsf{out}} = \int \iota(\varepsilon) \, \exp\left[-\mu(\varepsilon) \, \int_{\ell} \alpha(x, y) \, \mathrm{d}\ell\right] \, \mathrm{d}\varepsilon.$$
(1b)

Polychromatic X-ray CT Model via Mass Attenuation

Assumption:

• Both incident spectrum $\iota(\varepsilon)$ and mass attenuation function $\mu(\varepsilon)$ of the object are unknown.

Objective:

• Estimate the density map $\alpha(x, y)$.

Based on the fact that mass attenuation $\mu(\varepsilon)$ and incident spectrum density $\iota(\varepsilon)$ are both functions of ε (see Fig. 1), our **idea** is to:

- write the model as integrals of μ rather than ε ;
- estimate $\iota(\mu)$ rather than $\iota(\varepsilon)$ and $\mu(\varepsilon)$.

For invertible $\mu(\varepsilon)$, define its inverse as $\varepsilon(\mu)$ and rewrite (1a) and (1b) as

$$\mathcal{I}^{\text{in}} = \int \iota(\mu) \, \mathrm{d}\mu, \qquad \mathcal{I}^{\text{out}} = \int \iota(\mu) \exp\left[-\mu \int_{\ell} \alpha(x, y) \, \mathrm{d}\ell\right] \mathrm{d}\mu \qquad (2)$$

where

$\mathfrak{\iota}(\mu) \triangleq \iota(\varepsilon(\mu))|\varepsilon'(\mu)|$

and $\varepsilon(\mu)$ is differentiable with derivative $\varepsilon'(\mu) = \frac{d\varepsilon(\mu)}{d\mu}$. Invertibility of $\mu(\varepsilon)$ is assumed for simplicity: easy to extend (2) to arbitrary $\mu(\varepsilon)$.

Discretizations over Mass Attenuation

Discretize (2) in the mass attenuation and spatial domains using J mass attenuation bins and p pixels:





Figure 1: Mass attenuation and incident spectrum as functions of photon energy ε .

X-ray path ℓ

Figure 2: Discretization over

space: $\int_{\ell} \alpha(x, y) d\ell \approx \phi^T \alpha$.



To leave some margin for the noise and discretization effects, we relax the nonnegative signal constraint $\alpha \succeq 0$ and propose the following penalized least-squares (LS) objective function:

$$L_{\nu,t}(\boldsymbol{\theta}) = \frac{1}{2} \|\boldsymbol{z} - \boldsymbol{f}(\boldsymbol{\theta})\|_{2}^{2} + \frac{\nu}{2} \|(-\boldsymbol{\alpha})_{+}\|_{2}^{2} + t \left[-\mathbf{1}_{J\times 1}^{T} \ln_{\circ}(\boldsymbol{\mathcal{I}}) - \ln\left(\boldsymbol{\mathcal{I}}_{MAX}^{\text{in}} - \mathbf{1}_{J\times 1}^{T}\boldsymbol{\mathcal{I}}\right)\right]$$
energy of negative pixels
log barrier penalty
(5)

where ν and t are scalar tuning constants for the signal nonnegativity and sparsity penalty terms. Notation: $(x)_{\perp}$ keeps positive elements of x intact and sets the rest to zero.

Minimization Algorithm: Define the gradient vectors $g_{\alpha,\nu}(\theta)$, $g_{\mathcal{I},t}(\theta)$ and Hessian matrices $H_{\alpha,\nu}(\theta)$, $H_{\mathcal{T},t}(\boldsymbol{\theta})$ of the objective function (5) with respect to $\boldsymbol{\alpha}$ and \mathcal{I} , respectively. Descend (5) by alternating between (i) and (ii):

(i) the Polak-Ribière *nonlinear conjugate-gradient* (ii) • if step for α [Shewchuk 1994, Sec. 14.1] w is fixed and set to $\mathcal{I}^{(i)}$;

$$\boldsymbol{\alpha}^{(i+1)} = \boldsymbol{\alpha}^{(i)} - s_{\boldsymbol{\alpha}} \frac{\boldsymbol{g}_{\boldsymbol{\alpha},\nu}^{T}(\boldsymbol{\theta}^{(i)}) \boldsymbol{d}^{(i)}}{\boldsymbol{d}^{(i)T} H_{\boldsymbol{\alpha},\nu}(\boldsymbol{\theta}^{(i)}) \boldsymbol{d}^{(i)}} \boldsymbol{d}^{(i)}$$

where

$$\begin{split} \boldsymbol{e}^{(i)} &= \boldsymbol{g}_{\boldsymbol{\alpha},\nu}(\boldsymbol{\theta}^{(i)}) - \boldsymbol{g}_{\boldsymbol{\alpha},\nu}(\boldsymbol{\theta}^{(i-1)}) \\ \beta^{(i)} &= \max \bigg\{ 0, \ \frac{\boldsymbol{g}_{\boldsymbol{\alpha},\nu}^{T}(\boldsymbol{\theta}^{(i)})\boldsymbol{e}^{(i)}}{\|\boldsymbol{g}_{\boldsymbol{\alpha},\nu}(\boldsymbol{\theta}^{(i-1)})\|_{2}^{2}} \bigg\} \\ \boldsymbol{d}^{(i)} &= \boldsymbol{g}_{\boldsymbol{\alpha},\nu}(\boldsymbol{\theta}^{(i)}) + \beta^{(i)}\boldsymbol{d}^{(i-1)}; \end{split}$$

$$\mathbf{1}_{N imes 1} - oldsymbol{z} + oldsymbol{f} oldsymbol{\widetilde{ heta}}^{(i)} ig) \succeq \mathbf{0}_{N imes 1}$$
 (6

IOWA STATE

UNIVERSITY

Vewton step for \mathcal{I} :

$$\mathcal{I}^{(i+1)} = \mathcal{I}^{(i)} - s_{\mathcal{I}} \Big[H_{\mathcal{I},t}(\widetilde{\boldsymbol{\theta}}^{(i)}) \Big]^{-1} g_{\mathcal{I},t}(\widetilde{\boldsymbol{\theta}}^{(i)})$$

where

$$\widetilde{oldsymbol{ heta}}^{(i)} = (oldsymbol{lpha}^{(i+1)}$$

• otherwise, i.e., if (6) does not hold, keep
the old
$$\mathcal{I}$$
:
 $\mathcal{I}^{(i+1)} = \mathcal{I}^{(i)}$.

Note: (6) ensures
$$H_{\mathcal{I},t}(\widetilde{\boldsymbol{ heta}}^{(i)}) \geq 0.$$

Numerical Example

Simulation example based on a binary 1024×1024 image in Fig. 5a obtained by thresholding the pixel values of a reconstruction in [Qiu and Dogandžić 2012, Fig. 5(b)].

- Inspected object, assumed to be made of iron, contains irregularly shaped inclusions; mass-attenuation function $\mu(\epsilon)$ for iron extracted from the NIST database.
- Polychromatic sinogram simulated using photon-energy discretization with 130 equi-spaced discretization points over the range 20 keV to 150 keV that approximates well the support of $\iota(\varepsilon)$.
- 1024-element measurement array employed.
- \blacktriangleright Radon transform Φ constructed using nonuniform fast Fourier transform (NUFFT) with full circular mask [Dogandžić et al. 2011].
- ▶ 180 equi-spaced parallel-beam projections with 1° spacing.
- ▶ Performance metric is the relative square error (RSE) of an estimate $\hat{\alpha}$ of the signal coefficient vector:

$$\text{RSE}\{\widehat{\boldsymbol{\alpha}}\} = 1 - \left(\frac{\widehat{\boldsymbol{\alpha}}^T \boldsymbol{\alpha}}{\|\widehat{\boldsymbol{\alpha}}\|_2 \|\boldsymbol{\alpha}\|_2}\right)^2.$$

We compare

- ▶ the traditional filtered backprojection (FBP) method, and
- ▶ our MAC reconstruction upon convergence of the iteration (i)–(ii)

Figs. 5f and 5g show the histograms of the residuals $z - \Phi \widehat{\alpha}_{\text{FBP}}$ and $z - f(\theta^{(+\infty)})$.



Figure 4: Simulated mass attenuation and incident X-ray spectrum as functions of the photon energy ε .

$$\square^{1}$$



່^ພ101 $(\underline{\omega})$ 10⁶



where
$$\mathcal{I}$$
 $\mathbf{1}_{N imes 1} - \mathbf{z}$
holds, apply the A

$$\mathcal{I}^{(i+1)} = \mathcal{I}^{(i)} - s_{\mathcal{I}} \Big[H_{\mathcal{I},t}(\widetilde{\boldsymbol{\theta}}^{(i)}) \Big]^{-1} g_{\mathcal{I},t}(\widetilde{\boldsymbol{\theta}}^{(i)})$$

 $\mathcal{I}^{(i)}$):

$$\mathcal{I}^{\mathsf{in}} = \sum_{j=1} \mathcal{I}_j \quad \mathsf{and} \quad \mathcal{I}^{\mathsf{out}} = \sum_{j=1} \mathcal{I}_j \mathrm{e}^{-\mu_j \, oldsymbol{\phi}^T oldsymbol{lpha}}$$

where

- $\triangleright \alpha$ is a $p \times 1$ column vector representing the 2-D image $\alpha(x, y)$ that we wish to reconstruct.
- $\blacktriangleright \phi$ is a $p \times 1$ vector of weights quantifying how much each element of α contributes to the X-ray attenuation on the straight-line path ℓ ,
- $\mu_0 < \mu_1 < \cdots < \mu_J$ are known discretization points along the μ axis, $\Delta \mu_j = \mu_j - \mu_{j-1}$, and
- $\blacktriangleright \mathcal{I}_j = \iota(\mu_j) \Delta \mu_j \approx \iota(\varepsilon_j) \Delta \varepsilon_j.$

The mass attenuation coefficient (MAC) discretization is facilitated by the following facts:

- \blacktriangleright μ of almost all materials at any energy level are within the range $10^{-2} \,\mathrm{cm}^2/\mathrm{g}$ to $10^4 \,\mathrm{cm}^2/\mathrm{g}$,
- the energy level of an X-ray scan is usually selected so that the function $\mu(\varepsilon)$ is as flat as possible. Choose discretization points $\{\mu_j\}_{i=1}^J$ with a sufficiently wide range to cover $\mu(\operatorname{supp}(\iota(\varepsilon)))$:

$$\mu_j = \mu_0 q^j, \qquad j = 1, 2, \dots, J.$$
 (4)

(3)

Identifiability:

- The value of μ_0 in (4) can be arbitrary,
- $\bullet \text{ if } \mathcal{I}_1 = 0, \ \mathcal{I}^{\mathsf{out}}\left((\boldsymbol{\alpha}, [\mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_J]^T)\right) \equiv \mathcal{I}^{\mathsf{out}}\left((\boldsymbol{\alpha} q, [\mathcal{I}_2, \mathcal{I}_3, \dots, \mathcal{I}_J, 0]^T)\right),$
- if $\mathcal{I}_J = 0$, $\mathcal{I}^{\mathsf{out}}((\boldsymbol{\alpha}, [\mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_J]^T)) \equiv \mathcal{I}^{\mathsf{out}}((\boldsymbol{\alpha}/q, [0, \mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_{J-1}]^T)).$

Hence, if the range of $\{\mu_j\}_{j=1}^J$ is sufficiently large to allow for zero edge elements of \mathcal{I} , then the recovery of α will be correct up to a scale of common ratio q.

Measurement Model, Assumptions, and Constraints

An X-ray CT scan consists of multiple projections with the beam intensity measured by multiple detectors, see Fig. 3. Model a vector \boldsymbol{z} of $N \log$ -scale noisy measurements as

$$oldsymbol{z} = oldsymbol{f}(oldsymbol{ heta}) + oldsymbol{n} = - ext{ln}_{\circ}[A(oldsymbol{lpha})oldsymbol{\mathcal{I}}] + oldsymbol{n}$$

where $\ln_{\circ}(\boldsymbol{x})$ denotes elementwise logarithm,

- $\blacktriangleright \mathcal{I} = [\mathcal{I}_1, \mathcal{I}_2, \dots, \mathcal{I}_J]^T$,
- $\blacktriangleright \left[A(\boldsymbol{\alpha})\right]_{i,j} = \exp(-\Phi_{(i)}^T \boldsymbol{\alpha} \mu_j),$
- $\Phi = [\Phi_{(1)} \Phi_{(2)} \cdots \Phi_{(N)}]^T$ is the Radon transform matrix for our imaging system, and
- n is additive white Gaussian noise.

Our goal: estimate the image and incident energy density parameters

$$oldsymbol{ heta} = ig(oldsymbol{lpha}, oldsymbol{\mathcal{I}}ig).$$

- **Assumptions:**
- Object's shadow covered by the receiver array;
- Known upper bound \mathcal{I}_{MAX}^{in} on incident energy \mathcal{I}^{in} : $\mathcal{I}^{in} = \sum_{j=1}^{J} \mathcal{I}_{j} = \mathbf{1}^{T} \mathcal{I} \leq \mathcal{I}_{MAX}^{in}$;
- ▶ $\iota(\mu)$ and $\alpha(x, y)$ are nonnegative for all ε , x and y: $\mathcal{I} \succeq \mathbf{0}$ and $\alpha \succeq \mathbf{0}$.

Notation: $y \succeq 0$ denotes that all elements of a vector y are nonnegative.

Figure 5: (a)–(c) The true image and FBP and MAC reconstructions, (d)–(e) corresponding 500th and 700th row profiles, and (f)-(g) residual histograms from the FBP and MAC reconstructions.

Future Work

- Generalize the proposed MAC discretization to handle multiple materials,
- Incorporate signal sparsity and develop an active set approach for estimating incident energy density parameters \mathcal{I} [Gu and Dogandžić 2013],
- Iteratively refine the selection of the mass attenuation discretization points $\{\mu_j\}_{j=1}^J$ based on the obtained estimates of \mathcal{I} .

References

- Aleksandar Dogandžić, Renliang Gu, and Kun Qiu. "Mask iterative hard thresholding algorithms for sparse image reconstruction of objects with known contour." Proc. Asilomar Conf. Signals, Syst. *Comput.* Pacific Grove, CA, Nov. 2011, pp. 2111–2116.
- Renliang Gu and Aleksandar Dogandžić. Sparse signal reconstruction from polychromatic X-ray CT measurements via mass attenuation coefficient discretization. Tech. rep. NSF/IU. Ames, IA: CNDE, Iowa State Univ., Mar. 2013.
- Francis A Jenkins and Harvey E White. Fundamentals of Optics. 3rd ed. New York: McGraw-Hill, 1957
- Kun Qiu and Aleksandar Dogandžić. "Sparse signal reconstruction via ECME hard thresholding." IEEE Trans. Signal Process. 60 (Sept. 2012), pp. 4551-4569.
- J. R. Shewchuk. An introduction to the conjugate gradient method without the agonizing pain. Tech. rep. CMU-CS-94-125. Pittsburgh, PA: Carnegie Mellon Univ., 1994.
- G. Van Gompel, K. Van Slambrouck, M. Defrise, K.J. Batenburg, J. de Mey, J. Sijbers, and J. Nuyts. "Iterative correction of beam hardening artifacts in CT." Med. Phys. 38 (2011), S36–S49.





