Iowa State University

Center for Nondestructive Evaluation

3D Volumetric Reconstruction from Incomplete X-Ray Projections

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Co-PI: Zhan Zhang

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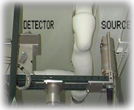

CENTER FOR NDE

Outline

Goals & Objectives

☞ DEVELOP X-ray CT reconstruction algorithms that will

- provide high-resolution artifact-free reconstructions from incomplete-data measurements

thanks to the use of

- signal constraints and priors and
- accurate statistical measurement and polychromatic source models.

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  thanks to the use of

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  - accurate statistical measurement and polychromatic source models.

- BUILD low-cost prototypes of 3D
  - straight-line-trajectory-based tomographic imaging (SLTTI),
  - computed laminography

  systems, with existing hardware!

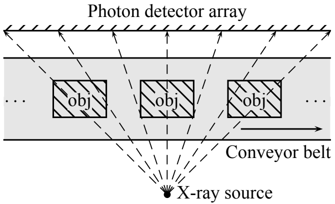


Figure 1: SLTTI system.

Why?

- In limited-angle CT configurations such as SLTTI (Fig. 2 top) or swing laminography (Fig. 2 bottom), some view angles are unavailable;
- some applications face the "bagel problem" where the specimen contains an X-ray opaque region.
- Solving the incomplete-data problem would enable the use of X-ray inspection in applications where it is not used today.

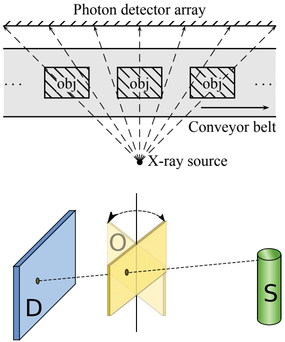
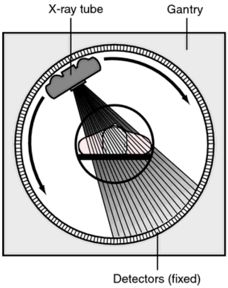
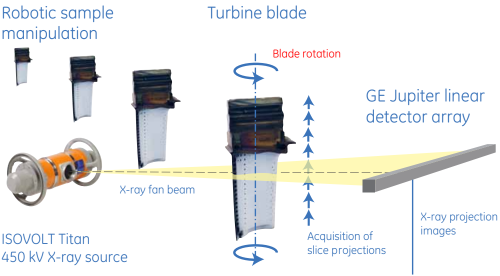


Figure 2: (Top) SLTTI and (bottom) limited-angle CT.

Third Generation Full-Angle X-ray CT Requires Rotation



(a) medical CT



(b) GE's system for CT turbine-blade inspection

Figure 3: Full-angle X-ray CT requires *rotational motion* of either (a) the X-ray source & detector (medical, security) or (b) the specimen (NDE).

SLTTI Systems Do Not Require Rotation

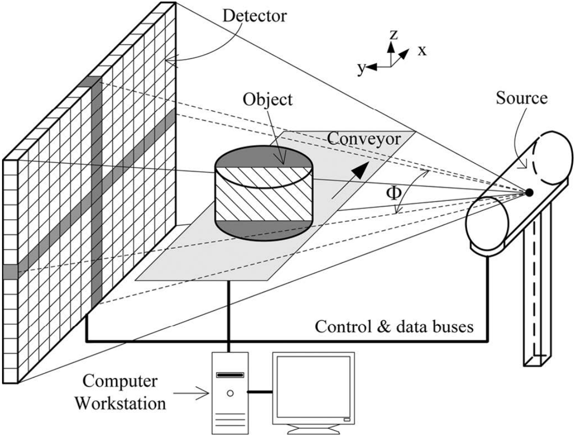


Figure 4: The source and detector are stationary, the object moves along a straight line.

Outline

Incomplete Data

- [Gao et al. 2013; O'Brien et al. 2016] review algorithms for incomplete-data reconstruction, with focus on
  - SLTTI and
  - computed laminography (CL).
- State of the art for SLTTI is the transform-based approach in [Gao et al. 2013].

Statistical Model-Based Reconstruction

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- Used in commercial scanners in medical imaging: GE's Veo;
- Not used in commercial NDE;

Statistical Model-Based Reconstruction for Incomplete Data

[Liao and Sapiro 2008] assume monochromatic measurements and use the standard linear measurement model in additive white Gaussian noise (AWGN);

- apply total-variation (TV) and state-of-the-art dictionary learning (DL) regularizations.

Statistical Model-Based Reconstruction for Incomplete Data

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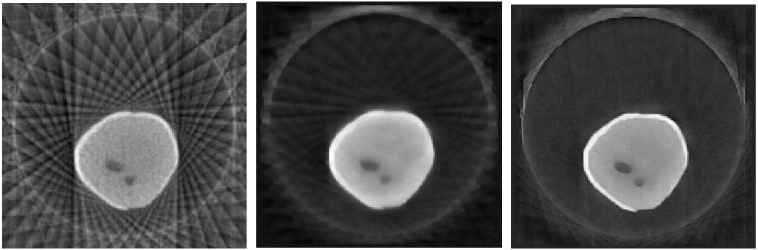
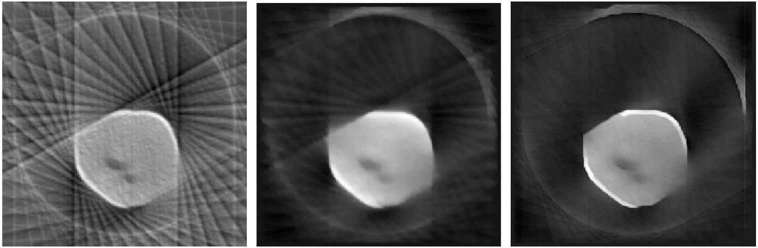
No work on polychromatic measurements *and* limited data.



(a) FBP (b) TV (c) DL

Figure 5: Reconstructions of a section of a tooth from 23 equi-spaced projections over 180°: (a) FBP and (b)–(c) statistical model based, TV and DL regularizations.

from [Liao and Sapiro 2008]



(a) FBP (b) TV (c) DL

Figure 6: Reconstructions of a section of a tooth from 15 equi-spaced projections over 120°: (a) FBP and (b)–(c) statistical model based, TV and DL regularizations.

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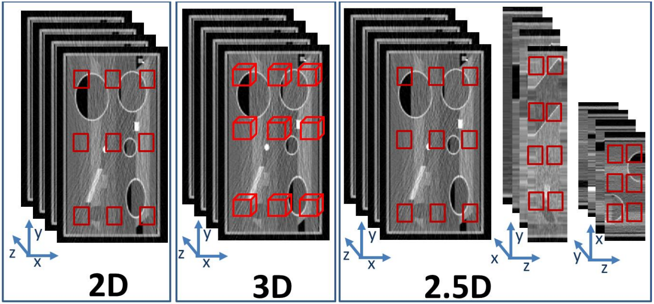
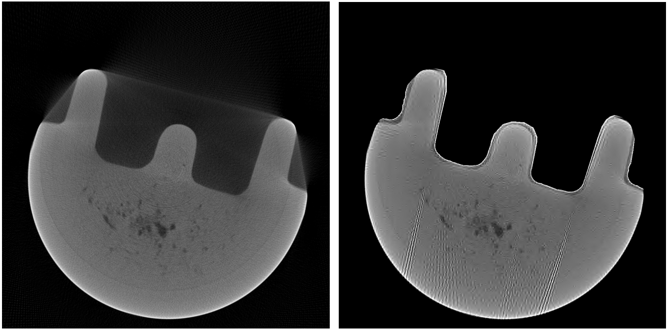
from [Liao and Sapiro 2008]

Image Patches for Regularization



Used in DL [Liao and Sapiro 2008; Luo et al. 2016] and machine-learning regularizations [Dong et al. 2014].

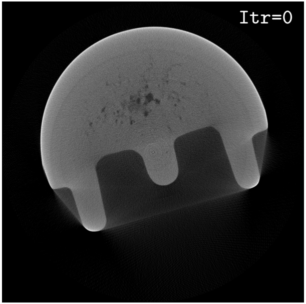
Problem with Linear-Model Based Reconstructions



(a) (b)

Figure 7: (a) FBP and (b) linear-model reconstructions from polychromatic X-ray CT measurements.

from [Gu and Dogandžić 2015]



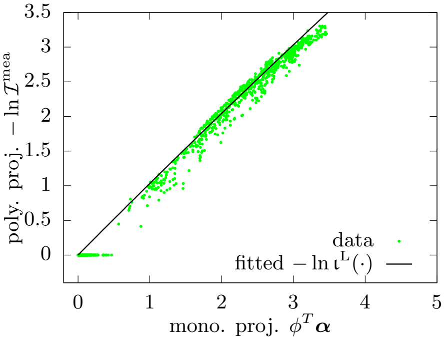


Figure 8: Our solution: blind nonlinear reconstruction [Gu and Dogandžić 2016].

Outline

1. Goals & Objectives
2. State of the Art
   - Incomplete data
   - Statistical model-based reconstruction
3. Technical Approach
   - Statistical model-based reconstruction
   - Transform-based reconstruction
   - Imposing constraints
4. Milestones & Deliverables

Technical Approach

1. Develop fast model- and transform-based CT reconstruction methods that incorporate
   - image constraints, e.g.,
     - nonnegativity of the density map [Gu and Dogandžić 2017],
     - inspected object's contour [Dogandžić et al. 2012];
   - machine-learning regularization [Dong et al. 2014; Liao and Sapiro 2008; Luo et al. 2016];
   - polychromatic models for reconstruction (developed in 2).

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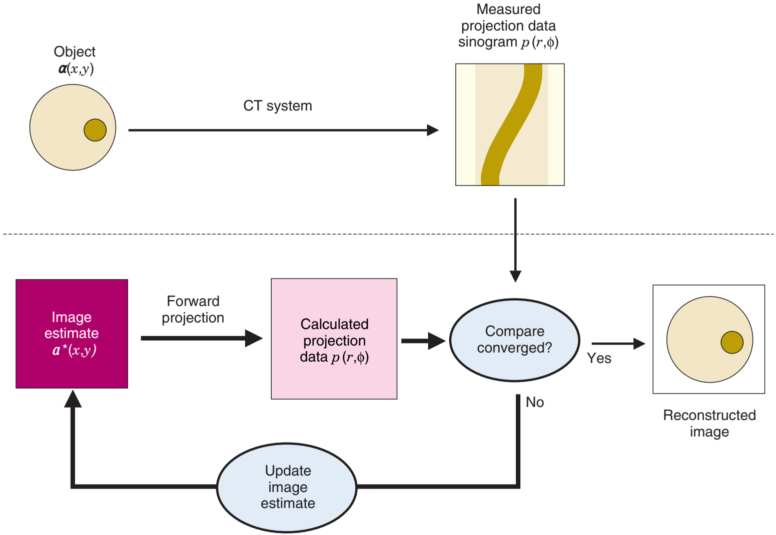
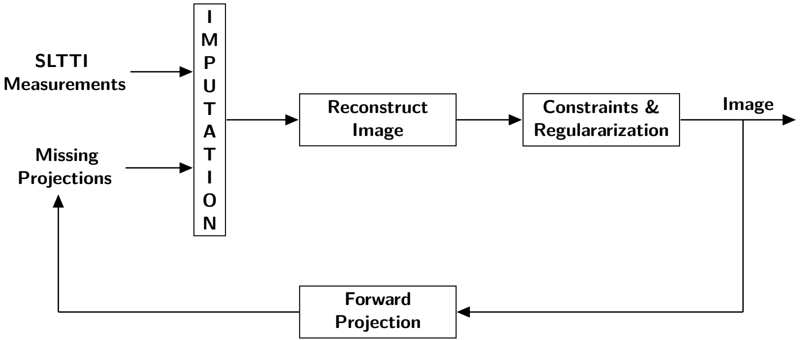
The incomplete-data scenario with polychromatic or polyenergetic measurements has received little attention.

Statistical Model-Based Reconstruction



Transform-Based Reconstruction



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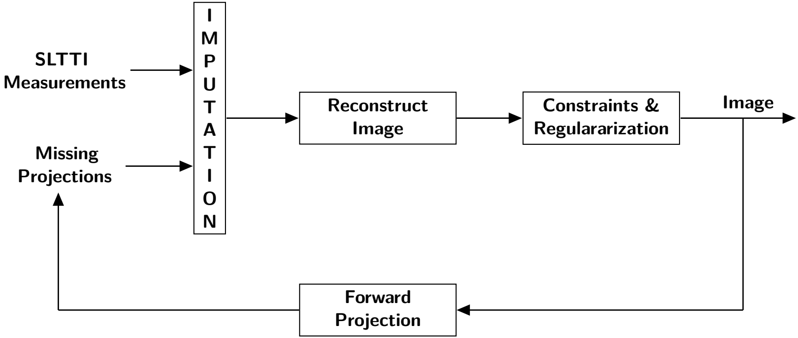
Transform-Based Reconstruction



☞ FASTER than statistical-model based approaches but inferior in reconstruction performance.

more

Statistical Model-Based Reconstruction With Set Constraints

- Minimize objective function $f(\boldsymbol{\alpha})$ with respect to image $\boldsymbol{\alpha}$.

$$f(\boldsymbol{\alpha}) = \mathcal{L}(\boldsymbol{\alpha}) + u[\rho(\boldsymbol{\alpha}) + I_C(\boldsymbol{\alpha})]$$

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- data fidelity term
  negative log-likelihood (NLL)

Statistical Model-Based Reconstruction With Set Constraints

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$$f(\boldsymbol{\alpha}) = \boxed{\mathcal{L}(\boldsymbol{\alpha})} + u[\rho(\boldsymbol{\alpha}) + I_C(\boldsymbol{\alpha})]$$

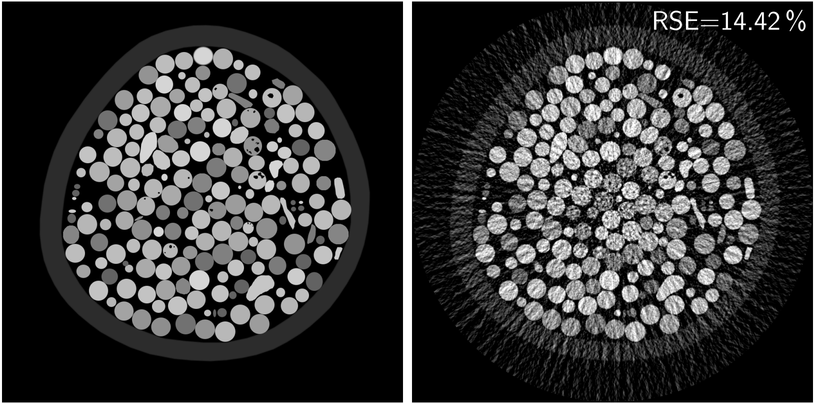
- data fidelity term
  negative log-likelihood (NLL)
- penalty term
  $u > 0$ is a scalar tuning constant
  $C \subseteq \mathrm{cl}\big(\mathrm{dom}\,\mathcal{L}(\boldsymbol{\alpha})\big)$

Composite Penalty

$$\rho(\boldsymbol{\alpha}) + I_C(\boldsymbol{\alpha})$$

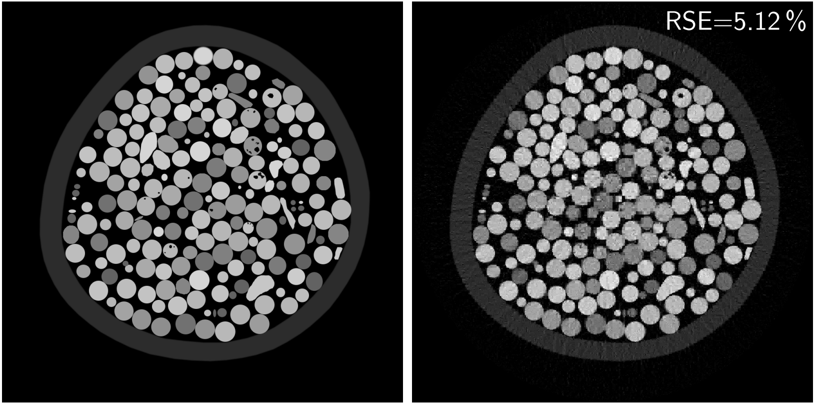
- $\rho(\boldsymbol{\alpha})$ is a finite penalty that imposes low-dimensionality of an appropriate transformed $\boldsymbol{\alpha}$ and
- set C imposes image constraints, e.g., nonnegativity:

$$C = \mathbb{R}^p_+.$$



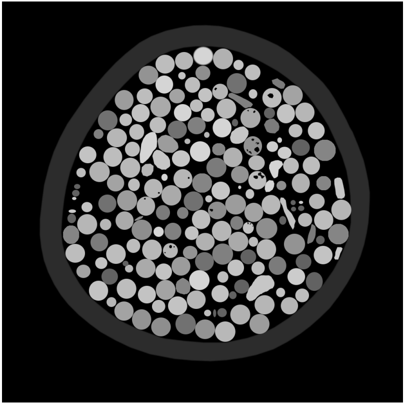
(a) ground truth (b) FBP

Figure 10: (a) Image of glass beads and (b) FBP reconstruction from 120 equi-spaced projections.

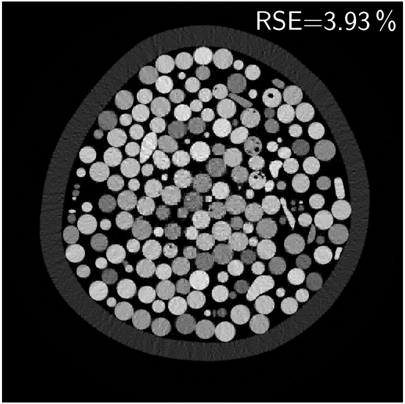


(a) ground truth (b) PNPG, $C = \mathbb{R}^p$

Figure 11: (a) Image of glass beads and (b) PNPG [Gu and Dogandžić 2017] reconstruction with TV regularization and $C = \mathbb{R}^p$.



(a) ground truth



(b) PNPG, $C = \mathbb{R}^p_+$

Figure 12: (a) Image of glass beads and (b) PNPG [Gu and Dogandžić 2017] reconstruction with TV regularization and $C = \mathbb{R}^p_+$.

Extracting and Using Geometric Object Information

- [Dogandžić et al. 2012] develop tools for incorporating geometric information about the inspected object into the reconstruction algorithms; see Fig. 13.
- Interestingly, [Liao and Sapiro 2008] also assume known contour of the inspected object, but do not discuss how to obtain such a contour. Such geometric information may be available *a priori*.

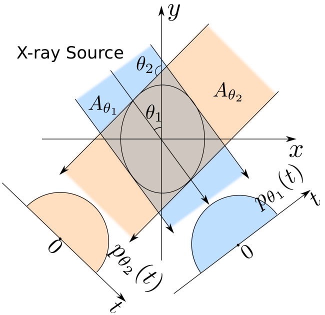


Figure 13: Sinogram can be used to extract the convex hull of the specimen.

Tasks

1. implement direct analytical 3D reconstruction algorithms (filtered backprojection (FBP)- and Feldkamp-Davis-Kress (FDK)-type and linogram) for missing-projection problems;
2. develop transform-based approaches and validate the reconstruction methods with XRsim results;
3. develop 3D SLTTI and laminography prototypes
4. develop statistical model-based algorithms
   - compare the results with transform-based algorithms using XRSim simulation and experimental data;
5. reconstruct multi-material objects
   - develop reconstruction algorithms for polychromatic and multi-energy scenarios and verify the effectiveness with both XRSim simulation and experimental data.

Outline

Key Milestones (2017–20)

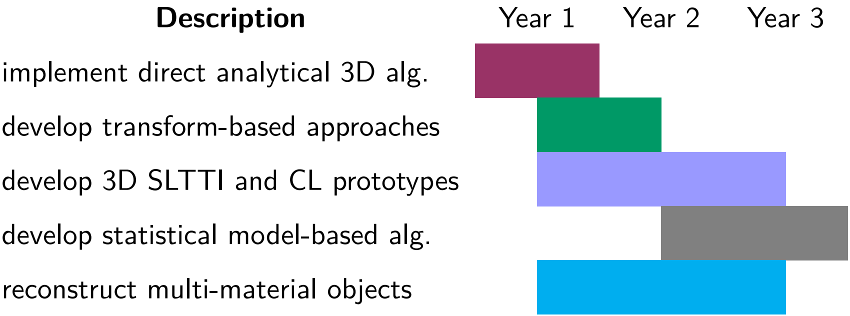
- Year 1:
  - implement direct analytical 3D reconstruction algorithms.
- Year 2
  - develop transform-based approaches for 3D volumetric limited data: SLTTI and CL;
  - develop polychromatic models for reconstruction.
- Year 3
  - develop statistical model-based reconstruction algorithms;
  - build SLTTI and CL prototypes;
  - develop polychromatic reconstruction algorithms.

Expected Deliverables

- Reconstruction software, XRsim update
- Polychromatic models for reconstruction
- Prototypes of SLTTI and CL systems.

We will incorporate the obtained preliminary results into proposals and seek external funding from, for example, Department of Homeland Security (DHS) and National Science Foundation (NSF).

Estimated Project Timeline & Plan



Outline Budget

$60K per year for three years. Funding will be used to

1. support a graduate student for three years,
2. partially support the PI and co-PIs' summer salaries (two weeks to one month per year),
3. cover travel costs to QNDE ($5K per year).

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Transform-based Reconstruction Methods

☞ IDEA [Nassi et al. 1982]: Iterate between

1. imputing the missing measurements
   - impose image constraints on the reconstruction and use the corresponding "model" sinogram,
   - the imputations *do not* account for the underlying probabilistic measurement model;
2. reconstructing the object using direct analytical reconstruction methods, such as the linogram, FBP, or FDK methods.

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