3D iterative helical targeted CT. Application to contrast-enhanced vascular imaging

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Introduction

Clinical problem

- Patient follow-up after stent implantation (in-stent restenosis, precise assessment of lumen size)
- Use of 3D helical CT angiography as minimally invasive alternative to IVUS & conventional angiography

Major challenges

- High accuracy required for clinical applications
- Presence of highly attenuating objects (metal mesh of the stent)
- Size of the problem, volume of computations

Contribution

- Clinical size data, geometry and acquisition modes
- Implementation on PC-type computers
- High accuracy

Key features

- Algebraic CT reconstruction method
- Parsimonious representation of 3D helical projection operator
- Targeted reconstruction framework
- Efficient optimization solver
- Polyenergetic data formation model

Method

Monoenergetic 3D CT reconstruction

- Data formation model: discretized approximation of Beer-Lambert law

$$\boldsymbol{y} = \mathbf{A}\boldsymbol{\mu} + \boldsymbol{b}$$

$\boldsymbol{y}$: projections; $\mathbf{A}$: projection matrix; $\boldsymbol{\mu}$: unknown object; $\boldsymbol{b}$: noise

- Optimization problem:

$$\begin{aligned} \hat{\mu} = \ & \arg\min_{\mu} \quad \tfrac{1}{2}\|\boldsymbol{y} - \mathbf{A}\boldsymbol{\mu}\|^2_{\Sigma} + \lambda R(\boldsymbol{\mu}) \\ & \text{subject to} \quad \boldsymbol{\mu} \geq 0. \end{aligned}$$

  - $\lambda R(\boldsymbol{\mu})$: convex edge-preserving regularization term
  - Very large, convex nonquadratic optimization problem

Targeted reconstruction

- Background / ROI decomposition

$$\boldsymbol{y} = \mathbf{A}^{\mathrm{bg}}\boldsymbol{\mu}^{\mathrm{bg}} + \mathbf{A}^{\mathrm{roi}}\boldsymbol{\mu}^{\mathrm{roi}} + \boldsymbol{b}$$

- Simple approach: subtraction of contribution of coarse or previously estimated background (*e.g.*, FBP or scanner reconstruction)

$$\boldsymbol{y}^{\mathrm{roi}} \stackrel{\mathrm{def}}{=} \boldsymbol{y} - \mathbf{A}^{\mathrm{bg}}\tilde{\boldsymbol{\mu}}^{\mathrm{bg}} = \mathbf{A}^{\mathrm{roi}}\boldsymbol{\mu}^{\mathrm{roi}} + \tilde{\boldsymbol{b}}$$

Optimization technique

- Characteristics of optimization problem: large, nonquadratic, convex
- Need for convergence control (accuracy). Rules out OS-type techniques
- Comparison of general purpose and specific convergent solvers
- Best all-around performance: L-BFGS-B

Projection operator

- Distance-driven: inadequate memory / computation trade-off
- Proposed representation
  - Thin-ray-driven operator
  - In 2D: efficient coding of segment end-points
  - 3D, helical MDCT extension
  - Efficient left and right matrix-vector products
  - *Multiple* thin rays per detector

Polyenergetic reconstruction

- Polyenergetic data formation model required in the presence of strongly attenuating objects
- Principle
  - Alvarez-Macovski decomposition: $\mu_e = \Phi(e)\phi + \Theta(e)\theta$
  - Heuristic analytic relationships from selected materials:

$$\phi = \phi(\mu_{70}) \ ; \ \theta = \theta(\mu_{70})$$

  - Parsimonious parameterization of the source spectrum
- Major hurdles
  - Complexity and difficulty of the optimization problem (non convexity, numerical conditioning, etc.)
  - Two projection / backprojection operations per iteration

Experimental results

Experimental setup

- Clinical MDCT: Siemens Somatom Sensation 16
- Acquisition protocol: 16 arrays, 672 detectors, 1160 views per rotation, angular FFS
- Physical multimodality vascular phantoms

Targeted reconstruction

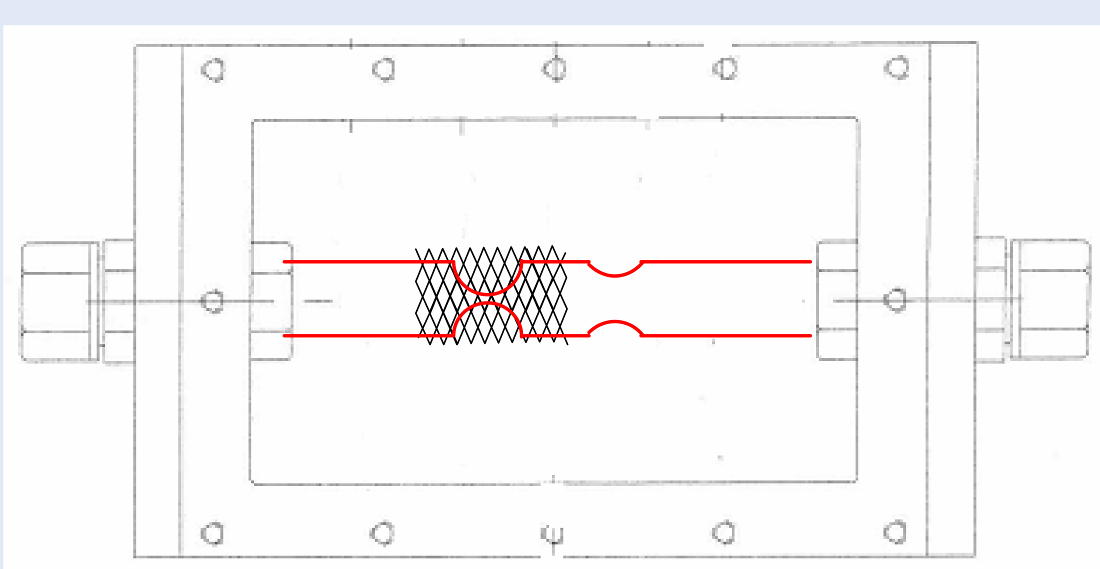
- Background: scanner reconstruction
- ROI: $128 \times 128 \times \approx 100$

Results

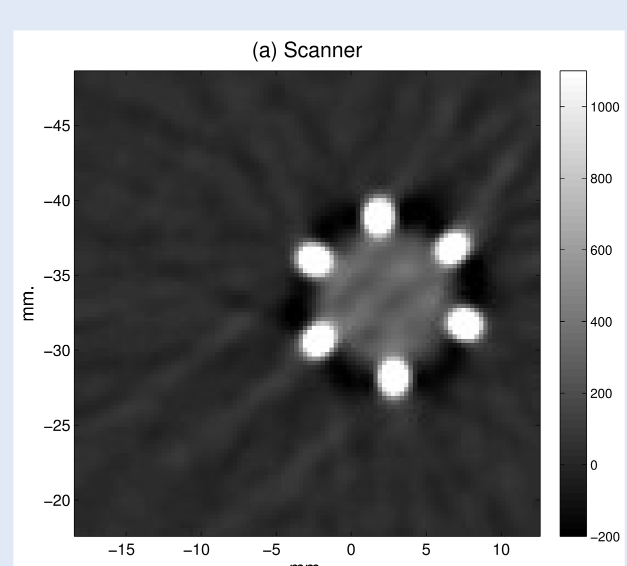
Computation times, $128 \times 128 \times 94$ ROI

	Monoenergetic	*Polyenergetic*
Total time	7 h 22 min	10 h 13 min
# iterations	96	61
# (proj. backproj.)	99	126

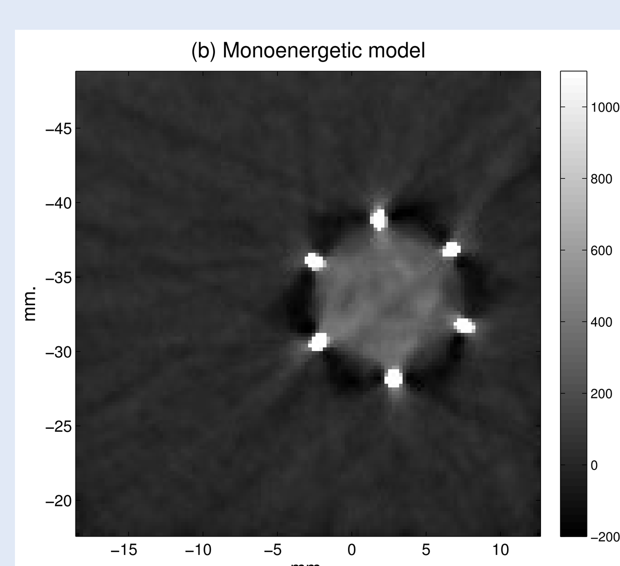
- Quality: randomized statistical study
  - Better assessment of shape and size by iterative reconstruction
  - Statistically significant advantage for polyenergetic reconstruction



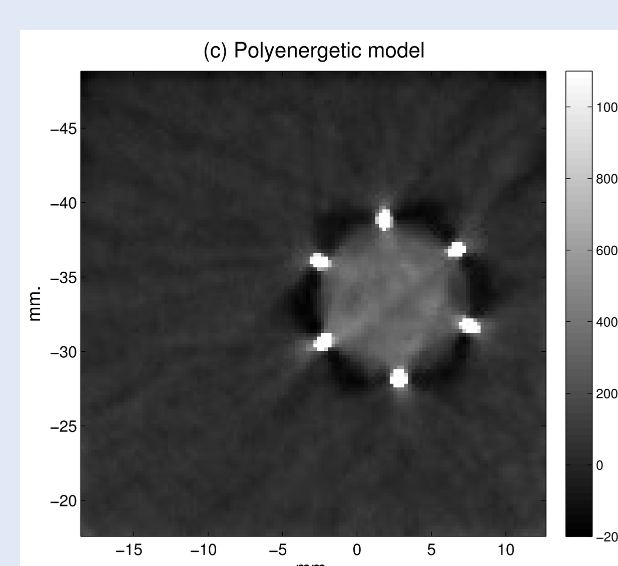
Vascular phantom



Scanner reconstruction



Monoenergetic model



Polyenergetic model

Conclusion

- Improved accuracy, robustness to the presence of metallic objects
- Niche applications already possible (vascular and orthopedic imaging)
- Further improvements in progress for wider applicability

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