Iterative Reconstruction in Transmission Computed Tomography: Innovations and Potential Applications

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Introduction

• Transmission Computed Tomography (CT)
• Fully 3D imaging modality
• Acquisition of hundreds projection images via partial attenuation of “some form of radiation”: X-rays, visible light
Introduction

• **X-ray CT:**
  • diagnostic radiology, EBRT treatment planning
  • on-board cone-beam CT (spatial conformity, IGRT)
• **Optical CT:** reading of radiosensitive gels for RT quality assurance (QA)
Bits of history

• **1917**: Radon transform formulated (theoretic work)
• **1971**: EMI scanner by Godfrey Hounsfield, iterative reconstruction on 80×80 image matrix

rsna.org

http://theinstitute.ieee.org

impactscan.org
Bits of history

• 1984:
  • Feldkamp-Davis-Kress (FDK) analytic algorithm for cone-beam CT
  • ML-EM iterative algorithm

• 2000-2005:
  • CBCT prototypes for linacs
  • rudimentary GPU codes for FDK and IR
  • more IR algorithms

• 2010 … :
  • CUDA API
  • wave of implementations
Motivation (why all the trouble?)

- FDK and the likes:
  - “good” images using considerable radiation doses and “nice” projections’ sets
  - quality quickly degrades in bad conditions

- IR
  - minor improvement of image quality for standard acquisitions
  - quantum leap: makes unusable projections’ sets usable
  - opens door to low-dose imaging and non-standard acquisitions
General concepts
Geometry modelling

- Image most often voxelized
- X-rays / visible light crossing the FOV
  - thin ray model (simple),
  - multi-ray (complex), most promising
  - thick ray model (even more complex).

Beister, Kolditz and Kalender, 2012

Fessler (AAPM course, 2011)
Physics modelling

- Beer-Lambert attenuation law, monochromatic

\[ I = I_0 \exp \left( -\sum_l l_j \mu_j \right) \]

- Interactions’ cross sections, polychromaticity

\[ \mu = \mu_C + \mu_{PE} \]

- Scattered radiation, Monte-Carlo simulations
Suppose detector reading a random variable e.g.:
- Normally distributed (many photons) OR
- Poisson-distributed (few photons)

Let the unknown $\mu$ parametrize the distribution

Select an estimator to find the parameter set (the 3D image !) e.g.:
- least squares
- maximum likelihood
Suppose detector reading a **random variable** e.g.:
- Normally distributed (many photons) OR
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Select an **estimator** to find the parameter set (the 3D image !) e.g.:
- least squares
- maximum likelihood

Some giant objective or “cost” function $F(\mu, I)$
Regularization term

- Noise or inconsistencies are expected…
- How to rectify a “bad voxel”?
- Look at the neighbors!
- A local penalization term is added to $F$
- Many edge-preserving regularization criteria available

E.g.: total variation minimization: suppose the image is composed of a majority of uniform regions
Solution

- Optimize the objective function $F$
- Plenty of methods from the **optimization** field e.g.:
  - steepest descent method (slow convergence)
  - incremental gradient descent (bias)
Implementation

- Iterative $\equiv$ sequential
  - 1 iteration is parallelizable
- Cost function depends on all voxel values
  - (cannot reconstruct small regions in parallel)
- Memory-intensive problem: sums up to compute a dot product and write the result to random memory locations.
Iterative reconstruction in X-ray CT
Disclaimer:
not an exhaustive review of IR
Dose reduction

- Regularized model-based IR robust to reduction of the number of projections
- Typical multislice scan: 1000-1200 projections
- CBCT: ~700 projections
- Jia et al., J. of XRay Sci and Tech, 2011
- Debatin et al., Fully3D Proceedings, 2013

Jia et al.

FDK
Dose reduction

- Matenine et al., Med Phys, 2015
- OSC-TV
  - ordered subsets convex (Kampuis and Beekman, 1998)
  - with TV regularization (Sidky et al., 2006)
  - with gradual subset number reduction
- rapid convergence + bias reduction at the end

- select a subset of projections
- simulate a number of direct projections through image estimate
- compute and apply image correction terms
Dose reduction

- Synthetic XCAT head phantom

slice size at reconstruction: 384\times384
z-range: 126 slices
Dose reduction

- Varian OBI Pelvis scan (half-fan)
  - bony structures well-defined
  - ring artifacts – “half-fan’s fault”
- OSC-TV beats POCS-TV (Sidky et al., 2006)
- less sensitive to free parameter variations

slice size at reconstruction: 416×416
z-range: 16 slices
Trends

• 4D-CBCT Iterative Reconstruction with deformable image registration e.g., Yan et al. Med Phys, 41(7), 2014
  • Deforming planning CT projections to match the CBCT and obtain quality phase images

* * * *

• Task-based dose optimization for model-based IR algorithms e.g., Li et al., Med Phys, 42(9), 2015)
  • Optimize kVp and mAs settings for specific lesion detection, based on local CNR
Survey!
HPC computing

- OSC-TV tested using the NVIDIA® Titan
  - 2688 cores
  - 1020 MHz max. clock
  - 288 GiB/s theoretical memory bandwidth
  - 32-bit floating point used
- OSC-TV recon times in the 1-3 min. range for limited volume coverage (15-100 slices)
- Pre-computed system matrix, data compression using geometric symmetries
- Current work: real-time raytracing
  - large cone opening
  - irregular angles during acquisition
HPC computing

• Memory-intensive problem poorly suited for distributed systems (MPI)
• Cloud computing (Amazon EC2), recon in 5 min for $10, see Rosen et al., Fully3D 2013
• Multi-GPU approaches
  • GPU cluster e.g., Guillimin/Helios
  • local machine
HPC computing

- Reconstruction toolkit (RTK) library based on the Insight Segmentation and Registration Toolkit (ITK).
  - [http://www.openrtk.org/](http://www.openrtk.org/)
- C++ library
- CMake cross-platform compilation
- CUDA support out of the box
- FDK, ART, SART implemented

Rit et al., J. of Physics: Conf Ser, 2014
IR in optical cone-beam CT
Optical CT

- Optical computed tomography (optical CT) is
  3D estimation of the attenuation of visible light in semi-transparent samples, very similar to X-ray CT

*it is not*

optical coherence tomography (OCT)
Optical CT

• Optical computed tomography (optical CT) is 3D estimation of the attenuation of visible light in semi-transparent samples, very similar to X-ray CT

  it is not optical coherence tomography (OCT)
  it is not diffuse optical imaging (DOI)
Optical CT

- Optical CT, primarily used in **gel dosimetry**\(^1\) for external beam radiation therapy

- Also, as an educational tool to emulate X-ray CT

\(^1\)Schreiner, “Where Does Gel Dosimetry Fit in the Clinic?”, 29 JPCS, 2009
Motivation

- Optical CT acquisitions most often reconstructed via filtered backprojection, no dose limits.
- Optical CT poses a set of **specific challenges**
  - physics
  - scanner designs
- IR methods tested on synthetic 2D optical CT data\(^2,3\), desirable to test on 3D real data


\(^3\)Doran and Yatigammana, “Eliminating the Need for Refractive Index Matching in Optical CT Scanners for Radiotherapy Dosimetry: I. Concept and Simulations”, PMB, 2012
DeskCAT scanner

- Educational tool for radiology, medical physics

63 cm
Cone beam optical CT

• Challenges related to physics
  • refraction at optical interfaces
  • scatter in colloids like gelatin
  • $n$ variations due to convection currents

• Challenges of the setup
  • opaque zones in the sample
  • moving debris
Phantoms, acquisitions

- Containers: plastic jars of 7.2 cm diameter
- Edge phantom: “transparent” + attenuating silicone
- Line pairs phantom, laser-printed on plastic
- Uniform phantom: water + food dye

- Scan:
  - 400 projections
  - $540 \times 120$ pixels
Results
Edge phantom reconstruction

320×320×64, [0, 0.5] cm⁻¹
Spatial resolution & noise

Edge profiles – FDK

Normalized $\mu$ (dimensionless)

Displacement from centre of line profile (mm)

- raw line profile
- curve fit

Normalized $\mu$ (dimensionless)
Spatial resolution & noise
Spatial resolution & noise

MTF estimated from curve fits

Note: OSC-TV yields 6 – 8 times lower noise $\sigma$ than FDK
Opaque line phantom recon.

FDK

OSC-TV

[-3, 5] cm⁻¹
Opaque line phantom recon.

[Graph showing halo artifact profiles for FDK and OSC-TV algorithms with position in mm on the x-axis and normalized \( \mu \) (dimensionless) on the y-axis.]
Uniform phantom reconstruction

FDK

OSC-TV
Uniform phantom reconstruction
Uniform phantom reconstruction

Measured spectra

Normalized LED intensity $W_e$

Wavelength (nm)

LED intensity

Dye solution $\mu$

(dimensionless)

$\mu$ (cm$^{-1}$)
Uniform phantom reconstruction

Light beam spectra in uniform phantom (10 ml added dye)

causes bias in $\mu$: 14-24%
c.f. gold standard
Conclusion

• OSC-TV offers:
  • Streaking artifact reduction (few-view)
  • Improved spatial resolution
  • Noise reduction
  • Halo artifact reduction (small opaque objects)

• Further work
  • Acceleration of the GPU code
  • Envisioned integration into the RTK library
  • 4D reconstruction
  • MC Scatter subtraction
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Appendix

• OSC-TV

Representative subset number reduction patterns for OSC-TV.