MRT Methodologies for Real-Time Simulation of Nuclear Systems

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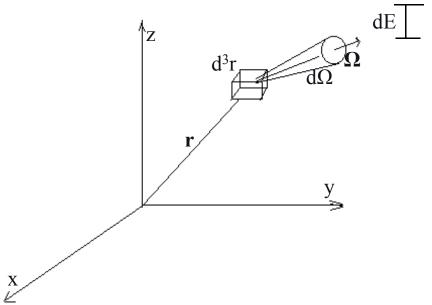


Particle Transport Theory

Objective

Determine the expected number of particles in a phase space ($d^3rdEd\Omega$) at time t:

$$n(\vec{r}, E, \hat{\Omega}, t)d^3rdEd\Omega$$



Number density is used to determine <u>angular flux/current</u>, <u>scalar flux and current</u> <u>density</u>, <u>partial currents</u>, <u>and reaction rates</u>.



Simulation Approaches

Deterministic Methods

Solve the linear Boltzmann equation to obtain the expected flux in a phase space

Statistical Monte Carlo Methods

 Perform particle transport <u>experiments</u> using random numbers (RN's) on a computer to estimate average properties of a particle in phase space



Deterministic – Linear Boltzmann Equation

• Integro-differential form

streaming collision $\hat{\Omega}.\nabla\Psi(\vec{r},E,\hat{\Omega}) + \sigma(\vec{r},E)\Psi(\vec{r},E,\hat{\Omega}) = \text{scattering}$ $\int_{0}^{\infty} dE' \int_{4\pi} d\Omega' \sigma_{s}(\vec{r},E' \to E,\hat{\Omega}' \to \hat{\Omega})\Psi(\vec{r},E',\hat{\Omega}) + \text{Independent source}$ $\frac{\chi(E)}{4\pi} \int_{0}^{\infty} dE' \int_{4\pi} d\Omega' \upsilon \sigma_{f}(\vec{r},E')\Psi(\vec{r},E',\hat{\Omega}) + S(\vec{r},E,\hat{\Omega})$

Integral form

$$\psi(\vec{r}, E, \hat{\Omega}) = \int_{0}^{R} d |\vec{r} - \vec{r'}| Q(r') e^{-\tau_{E}(\vec{r}, \vec{r'})} + \psi(\vec{r}_{s}, E, \hat{\Omega}) e^{-\tau_{E}(\vec{r}, \vec{r'})}$$

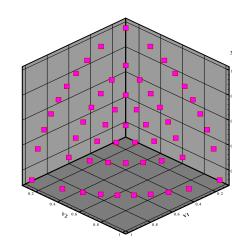


Integro-differential - Solution Method

• Angular variable: Discrete Ordinates (Sn) method:

A discrete set of directions $\{\hat{\Omega}_m\}$ and associated weights $\{\mathbf{w_m}\}$ are selected

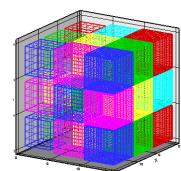
$$\hat{\Omega}_{m}.\nabla\Psi(\vec{r},E,\hat{\Omega}_{m}) + \sigma(\vec{r},E)\Psi(\vec{r},E,\hat{\Omega}_{m}) = q(\vec{r},E,\hat{\Omega}_{m})$$



Spatial variable

Integrated over <u>fine meshes</u> using FD or FE methods

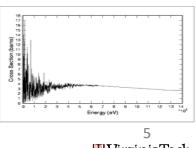
$$\Psi_{m,g,A} = \frac{\int d^3 r \Psi_{m,g}(\vec{r})}{\Delta V_{ijk}}$$



Energy variable

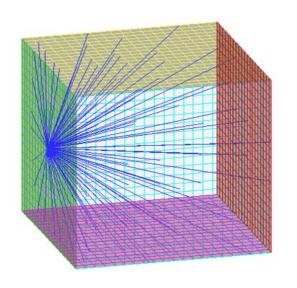
Integrate over energy intervals to prepare multigroup cross sections, $\sigma_{\!\scriptscriptstyle g}$

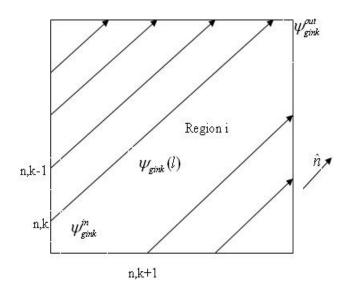




Integral - Solution method

Method of Characteristic (MOC): Model is partitioned into coarse meshes and transport equation is solved along the characteristic paths (k) (parallel to each discrete ordinate (n)), filling the mesh, and averaged





$$\psi_{g,m,i,k}(t_{m,i,k}) = \psi_{g,m,i,k}(0) \exp(-\sigma_{g,i}t_{m,i,k}) + \frac{Q_{g,m,i}}{\sigma_{g,i}}(1 - \exp(-\sigma_{g,i}t_{m,i,k}))$$



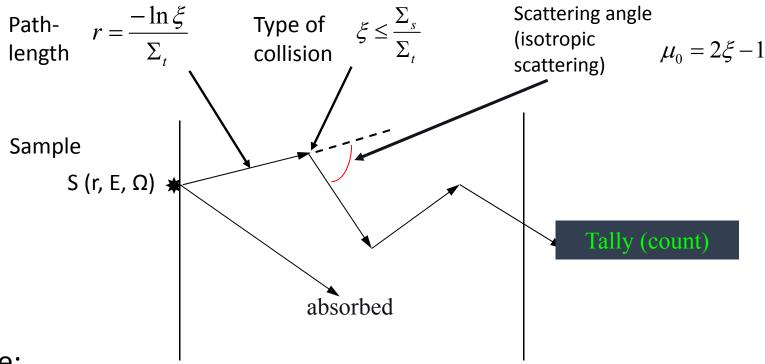
Deterministic - Issues/Challenges/Needs

- Robust <u>numerical</u> formulations (e.g., adaptive differencing strategy)
- Algorithms for improving <u>efficiency</u> (i.e., acceleration techniques
 synthetic formulations and pre-conditioners)
- Use of advanced computing <u>hardware & software</u> environments
- Pre- and post-processing tools
- > Multigroup cross section preparation
- Benchmarking



Monte Carlo Methods

 Perform an experiment on a computer; "exact" simulation of a physical process



Issue:

Precise expected values; i.e., small relative uncertainty, $R_{\overline{x}} = \frac{\sigma_{\overline{x}}}{\overline{x}}$

Variance Reduction techniques are needed for real-world problems!



Deterministic vs. Monte Carlo

Item	Deterministic	MC	
Geometry	Discrete/ Exact	Exact	
Energy treatment – cross section	Discrete	Exact	
Direction	Discrete/ Truncated series	Exact	
Input preparation	Difficult	simple	
Computer memory	Large	Small	
Computer time	Small	Large	
Numerical issues	Convergence	Statistical uncertainty	
Amount of information	Large	Limited	
Parallel computing	Complex	Trivial	



Why not MC only?

 Because of the difficulty in obtaining detail information with reliable statistical uncertainty in a reasonable time

Example situations

- Real-time simulations
- Obtaining energy-dependent flux distributions,
- Time-dependent simulations,
- Sensitivity analysis,
- Determination of uncertainties



Why not use advanced hardware?

➤ VT³G has developed vector and parallel algorithms, and developed two large codes: PENTRAN (1996) and TITAN (2004)

Why not hybrid methods?

- Deterministic-deterministic (differencing schemes, different numerical formulations, generation of multigroup cross sections, generation of angular quadratures, acceleration techniques) (VT³G has developed various algorithms; a few have been implemented in PENTRAN and TITAN)
- ➤ Monte Carlo-deterministic (variance reduction with the of use deterministic adjoint) (VT³G has developed CADIS, A³MCNP in 1997; CADIS has become popular recently!)



1986- 1989	 Vector computing of 1-D Sn spherical geometry algorithm Development an adjoint methodology for simulation TMI-2 reactor 	Prof. Haghighat	
1989- 1992	 Vector and parallel processing of 2-D Sn algorithms Simulation of Reactor Pressure Vessel (RPV) 	Prof. R. Mattis, Pitt. Prof. B. Petrovic, GT	United States
1992- 1994	 Parallel processing of 2-D Sn algorithms & Acceleration methods Determination of uncertainties in the RPV transport calculations 	Dr. M. Hunter, W Prof. B. Petrovic, GT	The Court State of St
1994- 1995	 3-D parallel Sn Cartesian algorithms Monte Carlo for Reactor Pressure Vessel (RPV) benchmark using Weight-window generator; deterministic benchmarking of power reactors 	Dr. G. Sjoden, DOD Dr. J. Wagner, ORNL	
1995- 1997	 Directional Theta Weight (DTW) differencing formulation PENTRAN (Parallel Environment Neutral Particle TRANsport) code system CADIS (Consistent Adjoint Driven Importance Sampling) formulation for Monte Carlo Variance Reduction A³MCNP (Automated Adjoint Accelerate MCNP) 	Dr. B. Petrovic Dr. G. Sjoden, DOD Dr. J. Wagner, ORNL	Space Angle
1997- 2001	 Parallel Angular & Spatial Multigrid acceleration methods for Sn transport Hybrid algorithm for PGNNA device PENMSH & PENINP for mesh and input generation of PENTRAN Ordinate Splitting (OS) technique for modeling a x-ray CT machine 	Dr. V. Kucukboyaci, W Dr. B. Petrovi, GT Prof. Haghighat Prof. Hgahighat	the fa
2001- 2004	 Simplified Sn Even Parity (SSn-EP) algorithm for acceleration of the Sn method RAR (Regional Angular Refinement) formulation Pn-Tn angular quadrature set FAST (Flux Acceleration Simplified Transport) PENXMSH, An AutoCad driven PENMSH with automated meshing and parallel decomposition CPXSD (Contributon Point-wise cross-section Driven) for generation of multigroup libraries 	Dr. G. Longonil, PNNL Dr. A. Patchimpattapong IAEA Dr. A. Alpan, W	
2004- 2007	 TITAN hybrid parallel transport code system & a new version of PENMSH called PENMSHXP ADIES (Angular-dependent Adjoint Driven Electron-photon Importance Sampling) code system 	Dr. C. Yi, GT Dr. B. Dionne, ANL	TITAN
2007- 2011	 INSPCT-S (Inspection of Nuclear Spent fuel-Pool Calculation Tool ver. Spreadsheet), a MRT algorithm TITAN fictitious quadrature set and ray-tracing for SPECT (Single Photon Emission Computed Tomography) FMBMC-ICEU (Fission Matrix Based Monte Carlo with Initial source and Controlled Elements and Uncertainties) 	W. Walters, PhD Cand. Dr. C. Yi, GT Dr. M. Wenner, W	SE 1859 1860 1797 1899 189 SE 1859 1896 1896 1896 1896 1896 1896 1896 189
2011- 2013	 New WCOS (Weighted Circular Ordinated Splitting) Technique for the TITAN SPECT Formulation Adaptive Collision Source (ACS) for Sn transport AIMS (Active Interrogation for Monitoring Special-nuclear-materials), a MRT algorithm 	K. Royston, PhD Cand. W. Walters, PhD Cand.	AIMS
2014- 2015	 TITAN-SDM - includes Subgroup Decomposition Method for multigroup transport calculation TITAN-IR - TITAN with iterative image Reconstruction for SPECT RAPID - Real-time Analysis for spent fuel Pool <i>in situ</i> detection 	N. Roskoff, PhD Stud. K. Royston, PhD Cand. W. Walters, PhD Cand.	a contribut à distribut montribut de l'annual di britani

₩VirginiaTech₂

Remarks

 Particle transport-based methodologies are need for real-time simulation

 Particle transport codes, even those parallel with hybrid algorithms, are slow because of large number of unknowns



Development of Transport Formulations for Real-Time Applications

- Physics-Based transport methodologies are needed:
- Developed Multi-stage, Response-function Transport (MRT) methodology
 - Based on problem physics partition a problem into stages (subproblems),
 - For each stage employ response method and/or adjoint function methodology
 - Pre-calculate response-function or adjoint-function using an accurate and fast transport code
 - Solve a linear system of equations to couple all the stages



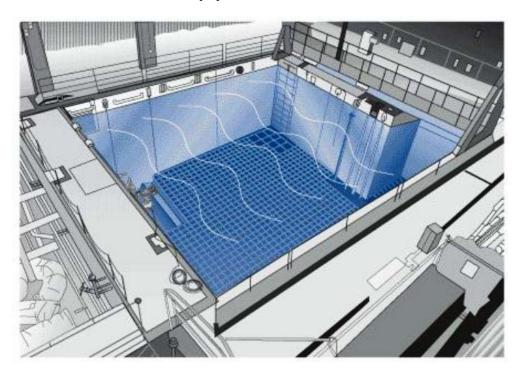
Examples for MRT Algorithms

- Nondestructive testing: Optimization of the Westinghouse's PGNNA active interrogation system for detection of RCRA (Resource Conversation and Recovery Act) (e.g., lead, mercury, cadmium) in waste drums (partial implementation of MRT; 1999)
- **Nuclear Safeguards:** Monitoring of spent fuel pools for detection of fuel diversion (2007) (funded by LLNL)
- **Nuclear nonproliferation:** Active interrogation of cargo containers for simulation of special nuclear materials (SNMs) (2013) (in collaboration with GaTech)
- **Spent fuel safety and security:** Real-time simulation of spent fuel pools for determination of eigenvalue, subcritical multiplication, and material identification (partly funded by I²S project, led by GaTech) (Ongoing)
- Image reconstruction for SPECT (Single Photon Emission Computed
 Tomography): Real-time simulation of an SPECT device for generation of project
 images using an MRT methodology and Maximum Likelihood Estimation
 Maximization (MLEM) (filed for a patent, June 2015)



Real-time simulations for commercial spent fuel pools

Criticality Safety, Nonproliferation & Safeguards applications





Background

- Standard approach Full Monte Carlo calculations face difficulties in this area
 - Convergence is difficult due to low coupling between regions (due to absorbers)
 - Convergence can also be difficult to detect
 - Computation times are very long, especially to get detailed information
 - Changing pool configuration requires complete recalculation
- Fission Matrix (FM) approach It can address the above issues
 - Fission matrix coefficients are pre-calculated using Monte Carlo
 - Computation times are much shorter, with no convergence issues
 - Detailed fission distributions are obtained at pin level
 - Changing pool assembly configuration does not require new precalculations
 - No additional Monte Carlo



Derivation of Fission Matrix (FM) Formulation

Eigenvalue formulation in operator form is expressed by

$$H\psi(\bar{p}) = \frac{1}{k}F\psi(\bar{p})$$

Where,

$$\begin{split} \bar{p} &= (\bar{r}, E, \widehat{\Omega}) \\ H &= \widehat{\Omega} \cdot \nabla + \sigma_t(\bar{r}, E) - \int_0^\infty dE' \int_{4\pi} d\Omega' \, \sigma_s(\bar{r}, E' \to E, \mu_0) \end{split}$$

$$F = \frac{\chi(E)}{4\pi} \int_0^\infty dE' \int_{4\pi} d\Omega' \, \nu \sigma_f(\bar{r}, E')$$



FM Derivation (cont)

We may rewrite above equation as

$$S(\bar{p}) = \frac{1}{k} A S(\bar{p})$$

Where,

$$S = \tilde{F}\psi$$
, $A = \tilde{F}H^{-1}\chi$, & $\tilde{F} = \frac{1}{4\pi} \int_0^\infty dE' \int_{4\pi} d\Omega' \nu \sigma_f(\bar{r}, E')$



Fission Matrix (FM) Formulation

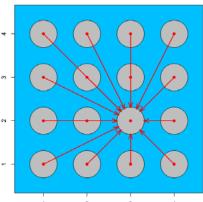
• Eigenvalue

$$F_i = \frac{1}{k} \sum_{j=1}^{N} a_{i,j} F_j$$



• F_i is fission source, S_i is fixed source in cell j

• $a_{i,j}$ is the number of fission neutrons produced in cell i due to a fig.



Subcritical multiplication

$$F_i = \sum_{j=1}^{N} (a_{i,j}F_j + b_{i,j}S_j^{Intrinsic}),$$

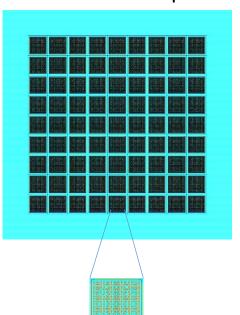
$$M = \frac{\sum_{j=1}^{N} (F_j + S_j^{intrinsic})}{\sum_{j=1}^{N} S_j^{intrinsic}}$$

• $b_{i,j}$ is the number of fission neutrons produced in cell i due to a source neutron born in cell j.

Developed a Multi-stage methodology for determination of FM coefficients

- As the computational size (for I²S reactor design)
 - $N = 9 \times 9 \times 336 = 27,216$ total fuel pins/ fission matrix cells
 - Considering 24 axial segments per rod, then
 - N = 653,184
- Standard FM would require N = 653,184 separate fixed-source calculations to determine the coefficient matrix
 - A matrix of size N x N = 4.26649E+11 total coefficients (> 3.4 TB of memory is needed)
- The standard approach is clearly NOT feasible
- We have developed a multi-stage approach to obtain detailed FM coefficients (in the process of filing for a patent)

9x9 array of assemblies in a pool



Assembly with 19x19 lattice; 25 positions are reserved for control rods



RAPID tool

- Developed the RAPID (Real-time Analysis spent fuel Pool In situ Detection) tool for determination of
 - Eigenvalue
 - Subcritical multiplication
 - Pin-wise, axial fission density
- With application to
 - Criticality safety
 - Safeguards
 - Nonproliferation and materials accountability



RAPID code system - Structure

Pre-Calculation (one time):

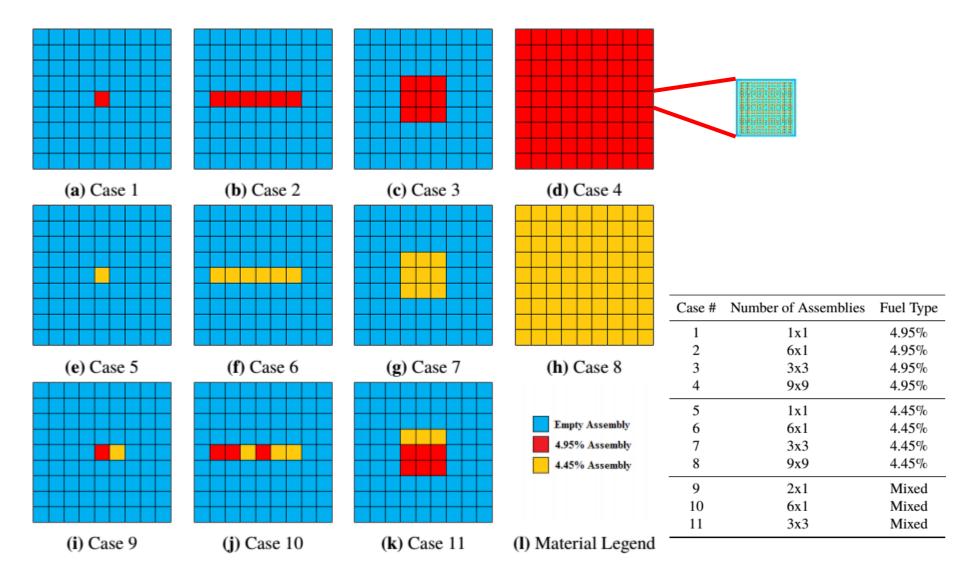
- 1. Burnup Calculation to obtain material composition
- 2. Fission Matrix Coefficient Generation

Real-time Analysis:

- 1. Run Fission Matrix Code
- 2. Process Results

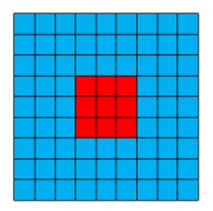


Test Problems (9x9 assemblies)

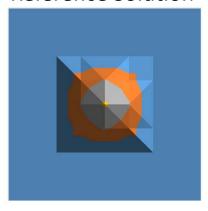




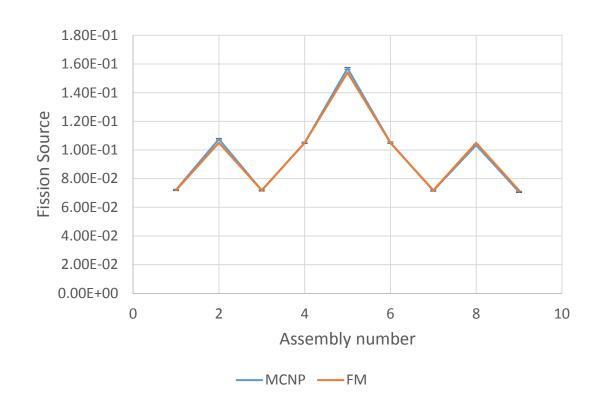
Case 3 Eigenfunction



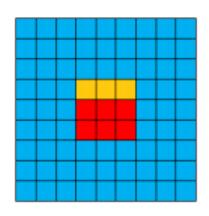
Reference Solution



Comparison of RAPID with MC



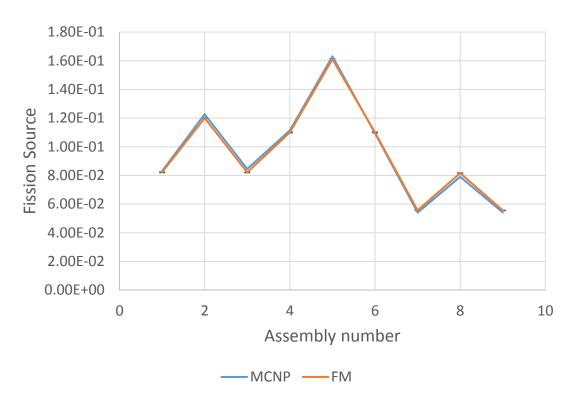
Case 11 Eigenfunction



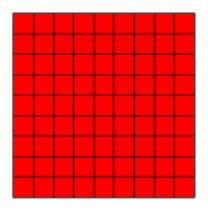
Reference Solution



Comparison with RAPID with MC



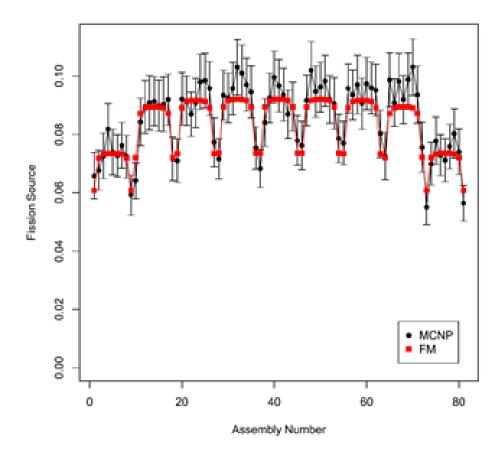
Case 4 Eigenfunction distribution



Reference Solution



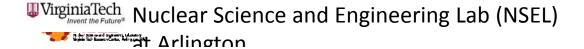
Comparison with RAPID with MC



Comparison of calculated M - RAPID vs. MCNP

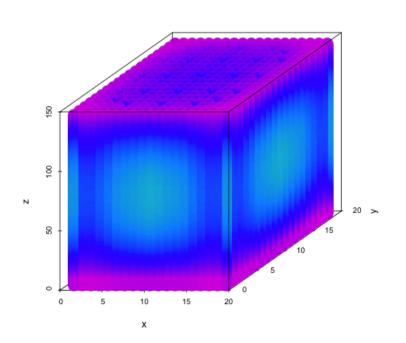
Case	FM		MCNP			Error in M	Speedup	
	M	Time (min)	M	Time (min)	1-σ Uncertainty	(FM vs MCNP)	(FM vs MCNP)	
1x1	3.343353	0.092	3.33155	925	0.0010	0.35%	10062	
6x1	4.328244	0.213	4.31336	1198	0.0010	0.35%	5613	
3x3	5.428051	0.965	5.40992	1502	0.0011	0.35%	1558	
9x9	6.697940	8.17	6.67674	1928	0.012	0.32%	236	

^{*}Note that the FM technique also provide pin-wise, axial-dependent fission source or power.

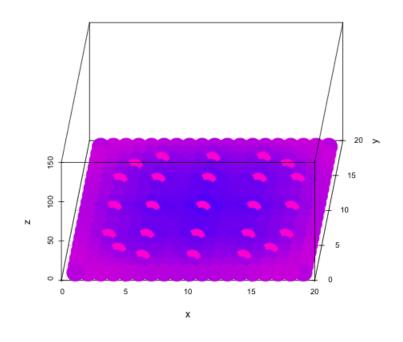


3-D Fission Density

Y-LEVEL ANIMATION



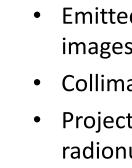
Z-LEVEL ANIMATION

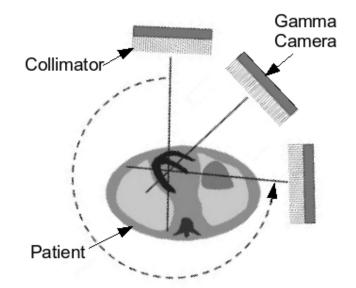




Introduction to Single Photon Emission Computed Tomography (SPECT)

- 17 million procedures in the US in 2010
- Nuclear medicine imaging procedure used to examine myocardial perfusion, bone metabolism, thyroid function, etc.
- Functional imaging modality
- Radiopharmaceutical injected/ingested and localizes in a part of the body
- Emitted radiation detected at a gamma camera to form 2D projection images at different angles
- Collimator in front of the gamma camera provides spatial resolution
- Projection images can be reconstructed to form a 3D image of the radionuclide distribution

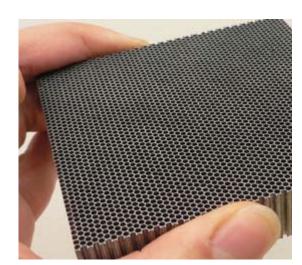




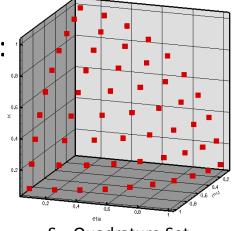


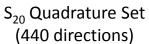
TITAN Deterministic SPECT Simulation

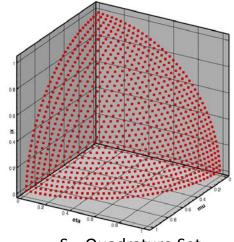
- The collimator in SPECT poses a challenge for deterministic modeling:
 - Spatial discretization
 - Angular discretization



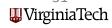
- Typical dimensions include:
 - Hole diameter ~0.18 cm
 - Septa thickness ~0.02 cm
 - Length ~3.3 cm
 - Acceptance Angle ~1.6°







S₈₆ Quadrature Set (7568 directions)₃₁





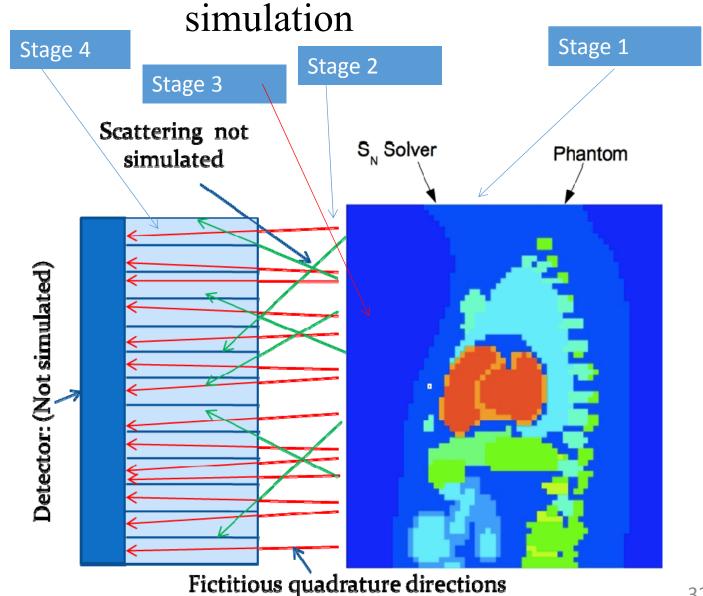
4-Stage TITAN Hybrid formulation for SPECT

Stage 1- Sn calculation in phantom

Stage 2 –
Selection of
fictitious angular
quadrature &
Circular OS (COS)
directions

Stage 3 – Sn with fictitious quadrature

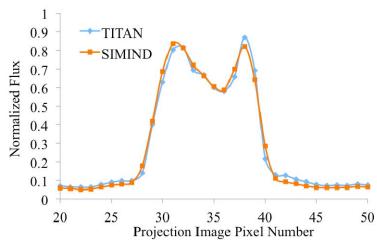
Stage 4 – ray tracing



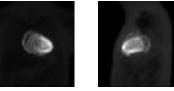
Example of Benchmarking TITAN Projection Images

SIMIND Comparison

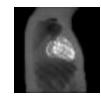
NURBS-based cardiac-torso (NCAT) phantom with Tc-99m (140 keV)



SIMIND generated projection images







Anterior

Left lateral

Posterior

Right lateral

TITAN generated projection images









Left lateral Posterior

Right lateral

Number of Projection Images	1	4	8	45	90
SIMIND Time (sec)	17	67	140	754	1508
TITAN Time (sec)	200	202	212	274	352

Times are for a single processor



Image Reconstruction

- Filtered backprojection (FBP) (Cormack 1963)
 - Analytic image reconstruction
 - Traditional standard for reconstruction due to speed and simplicity
 - Issues: filter choice, amplification of high-freq. noise, streak artifacts, cannot incorporate system details
- Algebraic reconstruction technique (ART) (Gordon et al. 1970)
 - Iterative constraint-based reconstruction
 - Allows the incorporation of prior knowledge
 - Issues: noisy, computationally expensive
- Maximum likelihood expectation maximization (ML-EM) (Shepp & Vardi 1982)
 - Iterative statistical reconstruction
 - For emission tomography, has recently surpassed FBP in popularity
 - Advantages include: Poisson statistics, nonnegativity constraint, incorporation of system details
 - Issues: increasing noise, computationally expensive



ML-EM Brief Derivation

Mean number of photons detected in detector bin *d*:

$$\overline{n}_d = \sum_{b=1}^B p_{b,d} \hat{\lambda}_b$$

 $p_{b,d}$: probability that photon emitted in voxel b is detected in bin d (system matrix) $\hat{\lambda}_b$: mean number of emissions in voxel b

Number of detected particles is a Poisson random variable, so the probability of detecting n_d^* photons in detector bin d:

$$P(n_d^*) = e^{-\bar{n}_d} \frac{\bar{n}_d^{n_d^*}}{n_d^*!}$$

Likelihood function:

$$L(\hat{\lambda}) = P(n_d^* \mid \hat{\lambda}) = \prod_{d=1}^{D} P(n_d^*) = \prod_{d=1}^{D} \frac{e^{-\overline{n}_d} \overline{n}_d^{n_d^*}}{n_d^*!}$$

Log-likelihood will have the same maximum location:

$$\ln(L(\hat{\lambda})) = \sum_{d=1}^{D} \left(-\overline{n}_{d} + n_{d}^{*} \ln(\overline{n}_{d}) - \ln(n_{d}^{*}!) \right)$$

$$= \sum_{d=1}^{D} \left[-\sum_{b=1}^{B} p_{b,d} \hat{\lambda}_{b} + n_{d}^{*} \ln(\sum_{b=1}^{B} p_{b,d} \hat{\lambda}_{b}) - \ln(n_{d}^{*}!) \right]$$

Take derivative and set to zero to find maximum:

$$\frac{\partial \ln(L(\hat{\lambda}))}{\partial \hat{\lambda}_{d}} = -\sum_{d=1}^{D} p_{b,d} + \sum_{d=1}^{D} \frac{n_{d}^{*}}{\sum_{b'=1}^{B} p_{b',d} \hat{\lambda}_{b'}} p_{b,d} = 0$$

Multiply by $\hat{\lambda}_{b}$ and solve:

$$\hat{\lambda}_{b}^{(i+1)} = \frac{\hat{\lambda}_{b}^{(i)}}{\sum_{d=1}^{D} p_{b,d}} \sum_{d=1}^{D} \frac{n_{d}^{*}}{\sum_{b'=1}^{B} p_{b',d}} \hat{\lambda}_{b'}^{(i)} p_{b,d}, \ b = 1, \square, B$$
 35

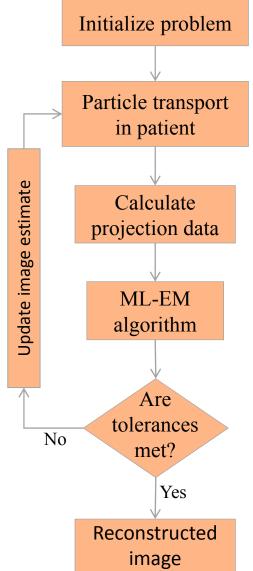


Deterministic Reconstruction for SPECT (DRS)

- Projection data calculated by deterministic transport code
- Particle transport fully modeled in patient for forward projection
- Detailed system matrix never needs to be created
- Backprojection uses simple system matrix

$$\hat{\lambda}_{b}^{(i+1)} = \frac{\hat{\lambda}_{b}^{(i)}}{\sum_{d=1}^{D} p_{b,d}} \sum_{d=1}^{D} \frac{n_{d}^{*}}{\hat{n}_{d}^{(i)}} p_{b,d}, b = 1, \square, B$$

 A script was developed to allow anyone to use this method with any code that creates projection data for a given source distribution





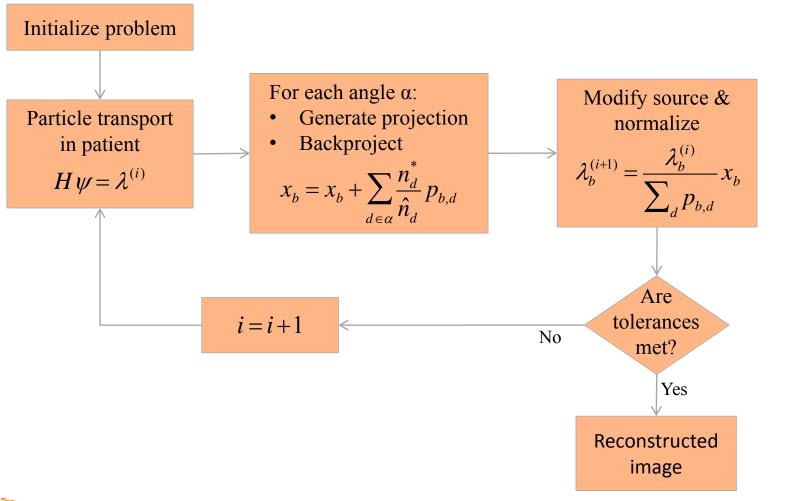
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TITAN with Image Reconstruction (TITAN-IR)

- Incorporate DRS methodology into TITAN code to take advantage of:
 - Fast generation of SPECT projection images
 - Parallel features
- Implement:
 - ML-EM reconstruction
 - Parallel image reconstruction
 - Image quality metrics (contrast and noise in reconstruction, mean relative error and mean squared error in projection data)
 - Post-reconstruction filtering



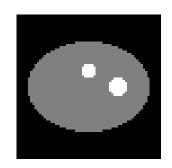
TITAN with Image Reconstruction (TITAN-IR)



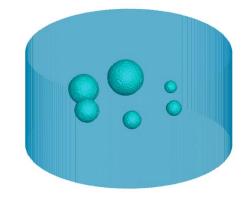


Analyzing TITAN-IR

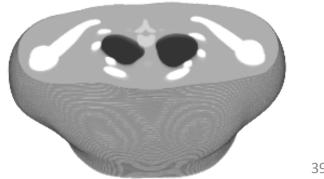
1) 2-D elliptical water phantom with two circles of high intensity source (i.e., lesions)



2) Jaszczak: 3-D quality assurance phantom, cold sphere region



3) NCAT: NURBS-based cardiactorso, 3-D heterogeneous phantom





Reconstruction Analysis

- Visually display reconstructed images
- Plot profiles through important areas of reconstructed images
- Quality metrics:

MRE =
$$\frac{1}{N_d} \sum_{d=1}^{N_d} \frac{\left| \hat{n}_d^{(i)} - n_d^* \right|}{n_d^*}$$

Mean squared error (MSE)

MSE =
$$\frac{1}{N_d} \sum_{d=1}^{N_d} (\hat{n}_d^{(i)} - n_d^*)^2$$

 $\hat{n}_d^{(i)}$ = counts in detector bin d at iteration i n_d^* = measured counts in detector bin d

Mean relative error (MRE) • Contrast
$$C_l = \frac{\overline{I_l} - \overline{I_0}}{\overline{I_0}}$$

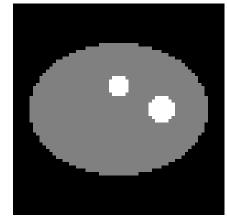
• Noise =
$$\frac{1}{\overline{I}_0} \left(\frac{\sum_{i=1}^{N_V} (I_i - \overline{I}_0)^2}{N_V - 1} \right)^{1/2}$$

 \overline{I}_{i} = average source intensity in lesion \overline{I}_0 = average reference background intensity

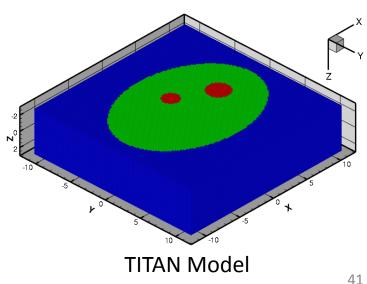


1) 2-D Phantom

- 2-dimensional, homogeneous, elliptical water phantom
- Tc-99m source (140 keV)
- Source strength of 2 in circles and 1 in rest of phantom
- 64 x 64 voxels (0.35 x 0.35 cm²)
- System matrix p(b,d) generated by Prof.
 Fessler's Image Reconstruction Toolbox*
 in MATLAB (models attenuation only)
- Reference projection images obtained at 120 angles over 360° using the SIMIND Monte Carlo code
- Initial guess is a uniform source distribution



Reference source distribution

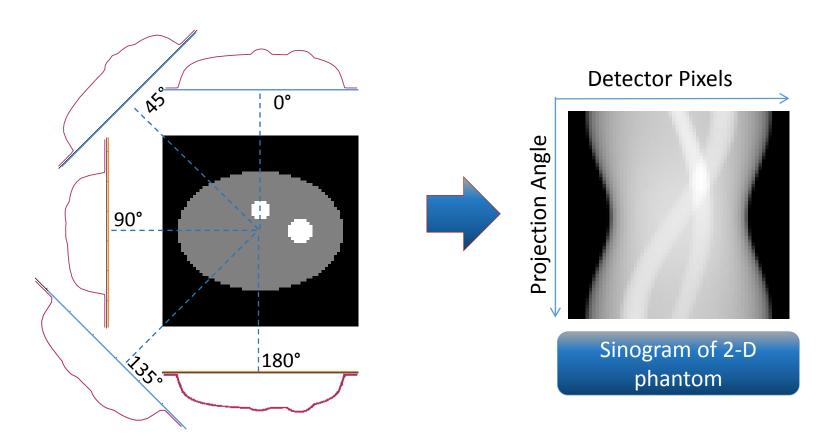




^{*}J. A. Fessler, "Image reconstruction toolbox," University of Michigan

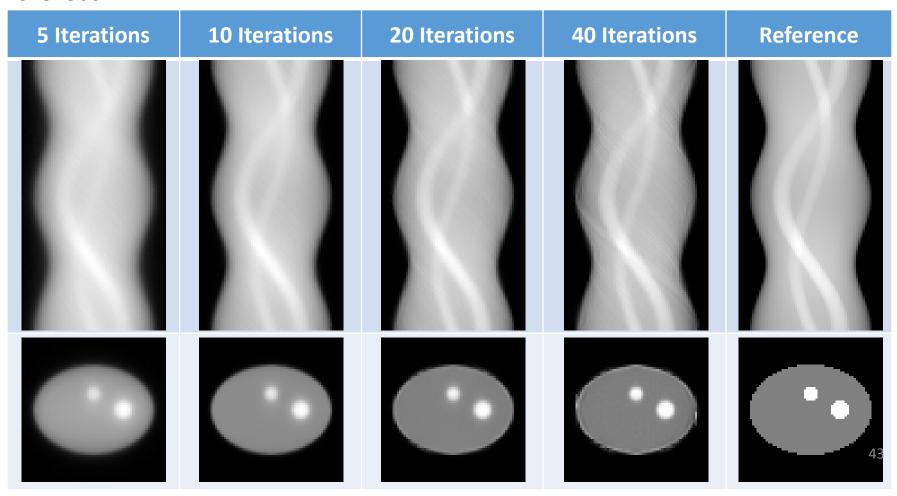
2-D Phantom

Reference projection data generated by the SIMIND Monte Carlo code* with no noise and a perfect collimator



2-D Phantom Image Reconstruction with TITAN

Reconstructed sinograms and images using TITAN for forward projection of 120 angles over 360°

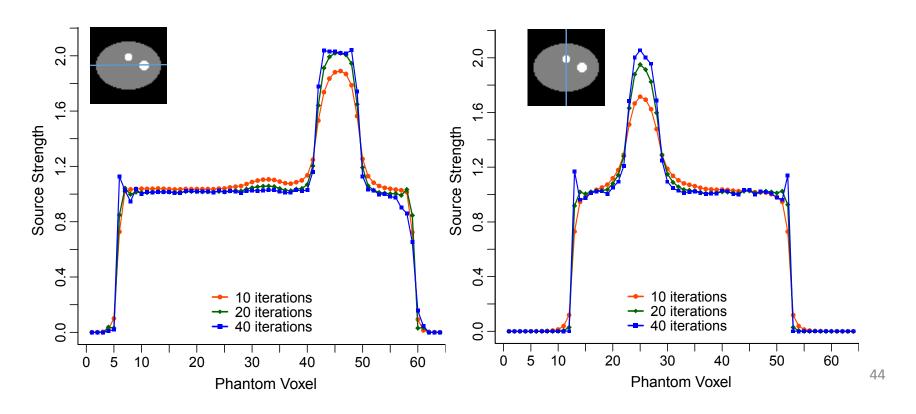




Royston and Haghighat, ANS RPSD 2014, Knoxville, TN

2D Phantom: Profiles Through Reconstruction with TITAN

Profiles through the reconstructed source distributions for different numbers of iterations





2D Phantom:

Comparing Reconstructed Images

Contrast (C_i) and Log-likelihood (I) as a function of number of iterations

$$C_l = \frac{\overline{I}_l - \overline{I}_0}{\overline{I}_0}$$

 \overline{I}_{i} = average source intensity in large circle

 \overline{I}_0 = average reference background intensity

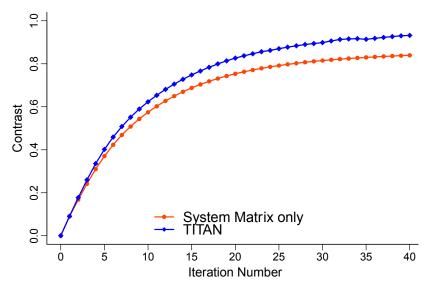
Likelihood =
$$L(\hat{\lambda}) = \prod_{d=1}^{D} \frac{e^{-\bar{n}_d} \bar{n}_d^{n_d^*}}{n_d^*!}$$

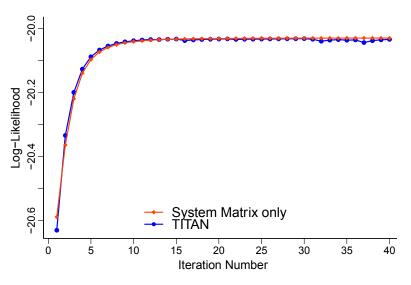
 $l(\hat{\lambda}) = \sum_{d=1}^{D} n^*(d) \log(\hat{n}(d)) - \sum_{d=1}^{D} \hat{n}(d)$

$$l(\hat{\lambda}) = \sum_{d=1}^{D} n^*(d) \log(\hat{n}(d)) - \sum_{d=1}^{D} \hat{n}(d)$$

 n^* = measured projection data

 \hat{n} = estimated projection data



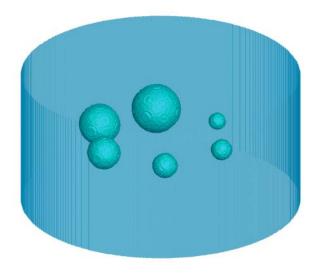




2) Jaszczak Cold Sphere Phantom

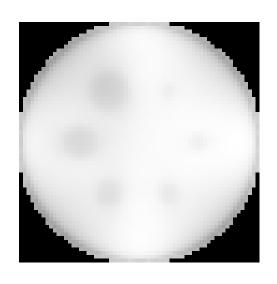
- 6 cold spheres with radii of 0.635, 0.795, 0.955,
 1.27, 1.59, and 1.9 cm
- 185 MBq Tc-99m source (140 keV)
- Reference projection data obtained at 64 angles over 360° using SIMIND
- System matrix p(b,d)
 - Generated by Image Reconstruction Toolbox in MATLAB (models attenuation but not scatter)
 - Dimensions of (64x64x32) by (64x32x64)
- Initial guess is a uniform source distribution
- Three cases of projection data:
 - 1) No noise & no collimator blur
 - 2) Noisy & no collimator blur
 - 3) Noisy collimated data

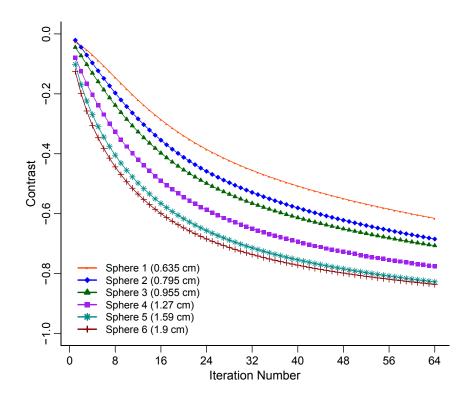






Jaszczak Phantom: Noiseless Projection Data with No Collimator Blur



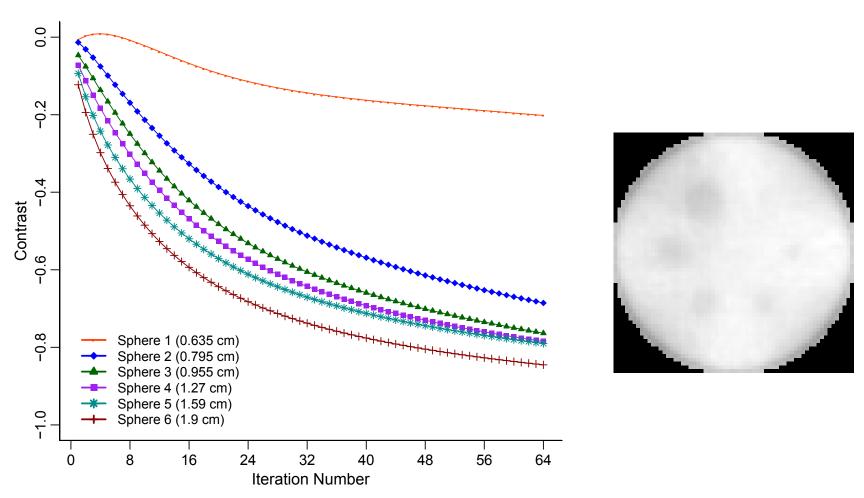


Contrast in cold spheres in center slice of TITAN-IR (S_6 , coarse mesh) image

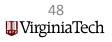




Jaszczak Cold Sphere Phantom: Noisy Projection Data with No Collimator Blur







Jaszczak Cold Sphere Phantom: Noisy Collimated Projection Data

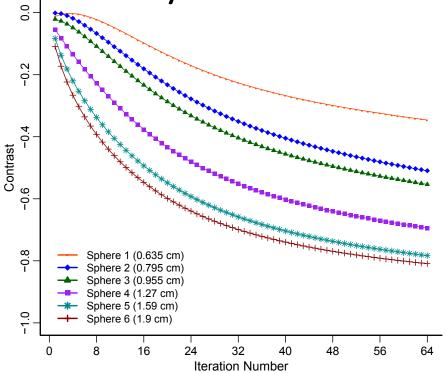
Collimator	Hole Diameter	Septa Thickness	Length	Acceptance Angle
GE-LEGP*	0.25 cm	0.03 cm	4.10 cm	1.83°
SE-LEHR [†]	0.111 cm	0.016 cm	2.405 cm	1.39°

^{*}General Electric – Low energy, general purpose collimator

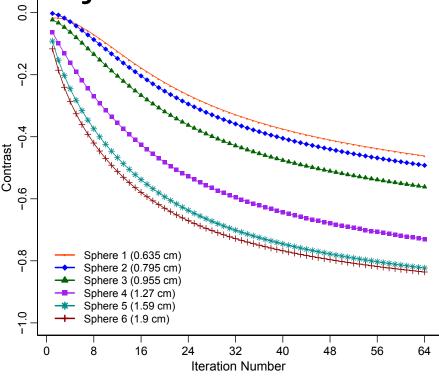


[†]Siemens – Low energy, high resolution collimator

Jaszczak Cold Sphere Phantom: Noisy Collimated Projection Data



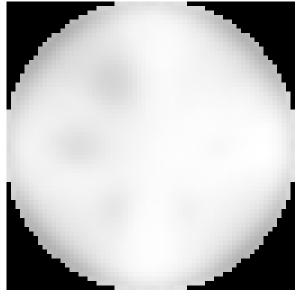
Contrast in each cold sphere (radius) for noisy GE-LEGP (1.83°) projection data



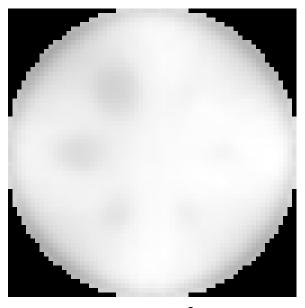
Contrast in each cold sphere (radius) for noisy SE-LEHR (1.39°) projection data



Jaszczak Cold Sphere Phantom: Noisy Collimated Projection Data



Reconstruction of noisy GE-LEGP data



Reconstruction of noisy SE-LEHR data



Comparison of TITAN-IR with Other Methods Based on Jaszczak Phantom:

- Filtered backprojection (FBP)
 - Traditional standard for image reconstruction
 - Implemented in MATLAB and includes the Chang attenuation correction*
- ML-EM with System Matrix (SM) only
 - Standard ML-EM reconstruction method
 - Algorithm written in Fortran 90
 - Uses the same system matrix that TITAN-IR uses for backprojection

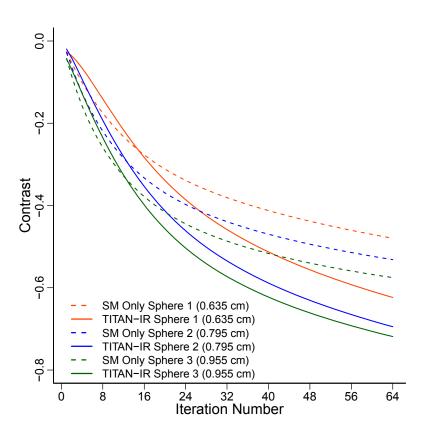


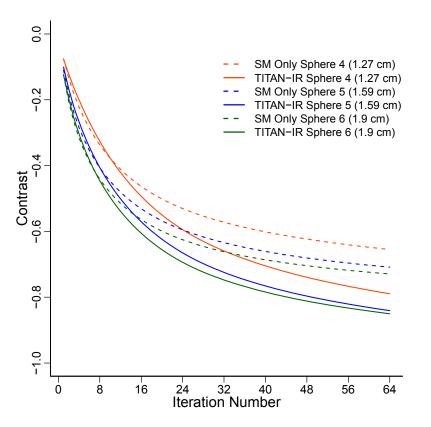
*L.-T.Chang, "A method for attenuation correction in radionuclide computed tomography," IEEE Trans. Nucl. Sci., 1978

Algorithm	Noiseless, no collimator blur	Noisy, no collimator blur	Noisy GE-LEGP	Noisy SE-LEHR
FBP				
ML-EM with SM only				
TITAN-IR				53



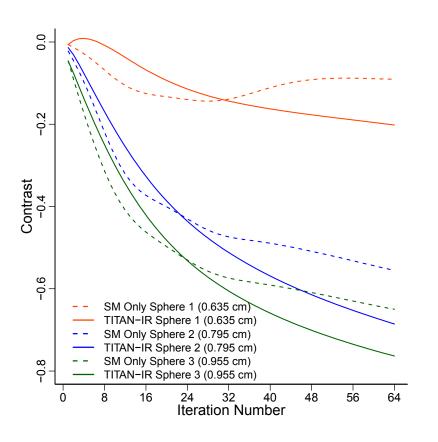
 Contrast in reconstruction of noiseless projection data with no collimator blur

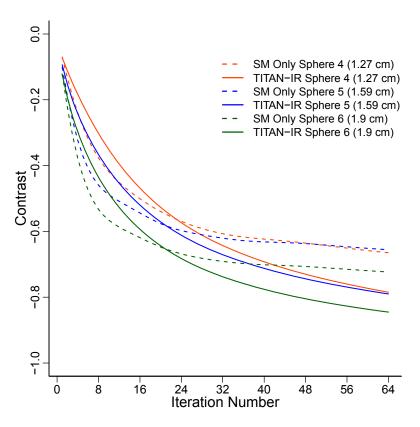






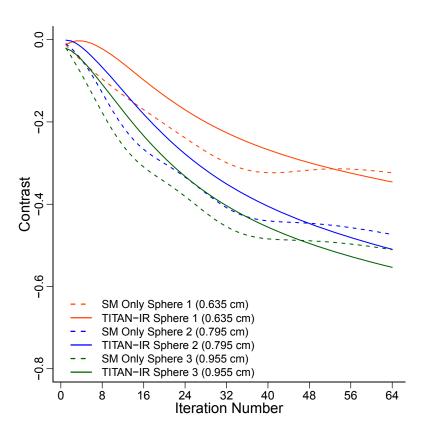
 Contrast in reconstruction of noisy projection data with no collimator blur

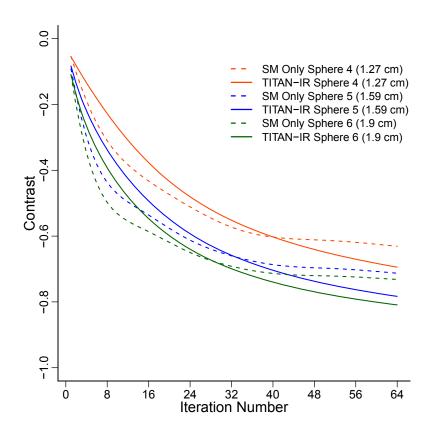






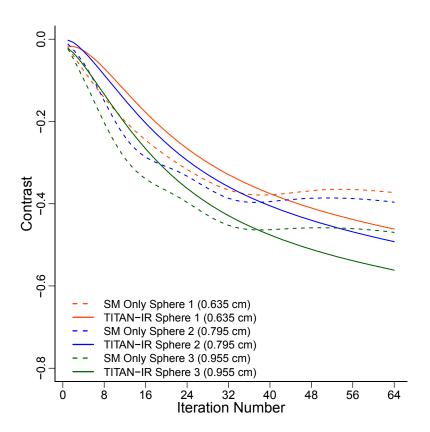
Contrast in reconstruction of noisy GE-LEGP projection data

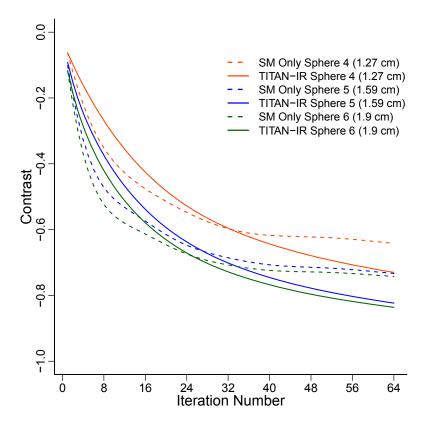




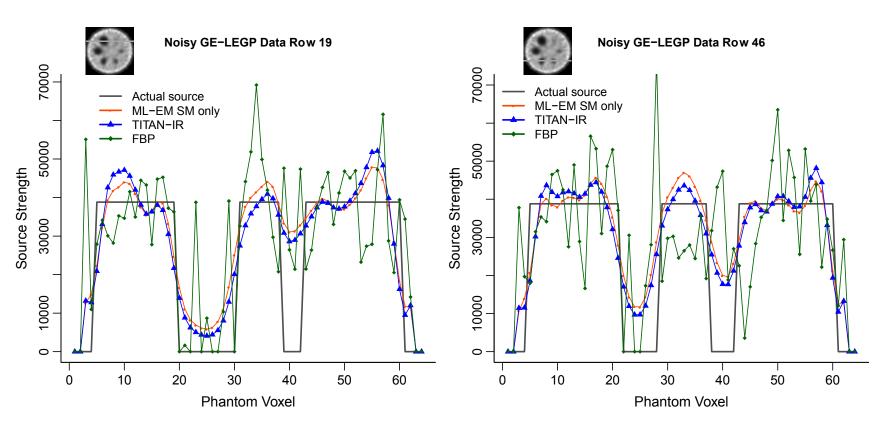


Contrast in reconstruction of noisy SE-LEHR projection data

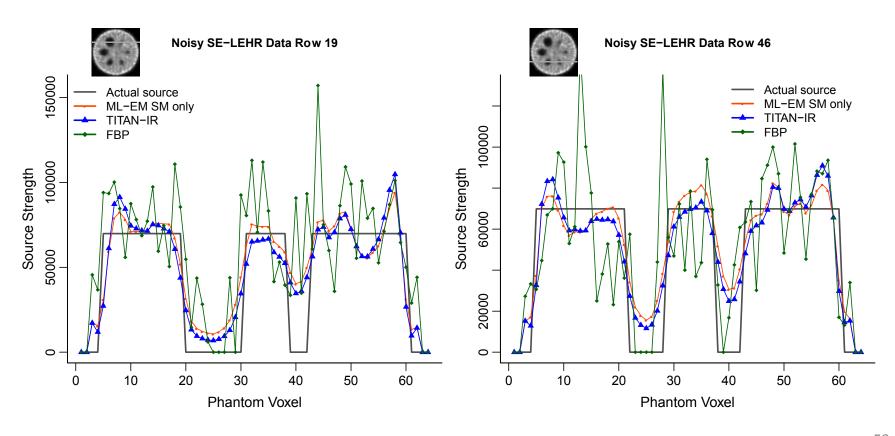














Computation Time

- To be viable for use in a clinical setting, as well as useful to researchers, computation time must be "reasonable"
- All calculations on a dedicated computer cluster:
 - Intel Xeon E5 2.6 GHz processors
 - 16 GB per processor core
 - 16 processor cores per compute node



Computation Time

Jaszczak phantom: TITAN-IR computation time for coarse meshing, S_6 , 64 iterations

Noiseless projection data with no collimator blur

Processor Cores	Wall Clock Time (s)	Speedup
1	575.7	-
2	291.5	2.0
4	149.9	3.8
8	81.4	7.1
16	36.8	15.6

Noisy GE-LEGP projection data

Processor Cores	Wall Clock Time (s)	Speedup
1	1665.7	-
2	905.1	1.8
4	524.3	3.2
8	341.4	4.9
16	172.0	9.7

Conclusion

MRT methodology allows for development of real-time tools for analysis of nuclear systems



Thanks!

Questions?

