Inference of Material Distribution from Exiting Radiation

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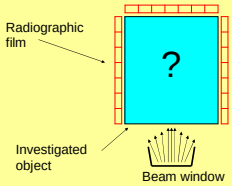
Abstract

An new approach is applied in a neutron tomography project. One key feature of this approach is that we treat the *material* as the unknown, as opposed to a set of *cross sections.* This changes the mathematical nature of the problem, and in fact greatly reduces the dimension of the search space. Another is that we take a hierarchical approach in which we learn some characteristics of the object from relatively crude (inexpensive) calculations, and then use knowledge from such calculations to guide successively more sophisticated calculations.

Introduction

The purpose of our project is to tell the inference of material properties inside an object based upon detection and analysis of radiation emerging from the object.



Minimization Based Approaches:

Objective Function:

$$\Phi = \frac{1}{2}\sum_{n=1}^{N}\left(M_n - P_n\right)^2$$

Where "P" treat as a function of properties of the unknown object

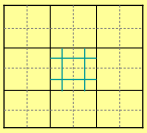
$$P = P\left(\sigma_t, \sigma_s, \sigma_{s1}, \cdots\right) \Rightarrow \Phi = \Phi\left(\sigma_t, \sigma_s, \sigma_{s1}, \cdots\right)$$

Drawbacks associated with continuous search approach:

- Deterministic method can be trapped into local minima
- Stochastic method is not always stable; also time consuming
- Cross-section sets obtained are not constrained to be realistic
- Dimension of space grows rapidly with more realistic models

Ideas

- Treat unknowns as materials instead of cross sections
- Systematic hierarchical approach
- Intelligent Sampling method (such as LHS)
- Advanced tabu-search techniques



Hierarchical Approaches:

Step 1: Gradient-based linear search for cross sections, using crude forward model (e.g. coarse-mesh one-group diffusion).

Step 2: Use results from Step 1 to restrict *material* search space for following step.

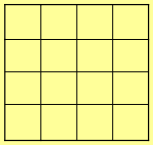
Step 3: Optimization with realistic transport forward model.

Combinatorial Optimization Problem

Suppose we divide an object into 4x4 cells in 2-D and we have 10 materials in our library of candidates. Then in each cell there are 10 possibilities, so over all there are

$$\underbrace{10\times10\times\cdots\times10}_{16\text{ times}} = 10^{16}$$

possible material distributions. This represents a combinatorial optimization problem. Note that the solution space is limit but *discrete*.



Results

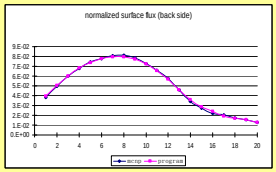


Fig 1. Comparison of MCNP "experiment" vs. S_N forward model.

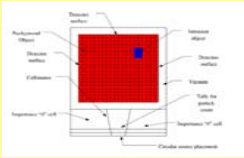


Fig 2. X-Y view of the object that produced Fig. 1.

- These figures show that our S_N transport model can reproduce MCNP results for a simple problem (Maxwellian incident energy distribution in MCNP; one energy group S_8 in model).
- We are working on steps 2 and 3 of our approach, but do not yet have results.
- We would be **very interested** in feedback on our ideas, and especially interested in previous work that may have used similar ideas.