

Domain Decomposition Methods for the Neutron Transport Equation

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Map of the talk

- ▶ Project aimed at developing and understanding numerical methods in radiative transport.
- ▶ Focus of this talk is the mono-energetic steady-state transport equation. (Equation on next slide)
- ▶ This talk is split into three parts:
 1. Source Iteration for the transport equation
 2. Benefits and limitations of diffusion synthetic acceleration,
 3. A domain decomposition approach to solving the transport equation.
- ▶ Motivation: domain decomposition methods have good parallelisation potential and can help improve convergence rate whilst limiting computational expense.

The problem

The (mono-energetic, steady-state) **neutron transport equation** in 5D with an isotropic source, $Q(\mathbf{r})$, is given by

$$\boldsymbol{\Omega} \cdot \nabla \psi(\mathbf{r}, \boldsymbol{\Omega}) + \sigma_T(\mathbf{r})\psi(\mathbf{r}, \boldsymbol{\Omega}) = \frac{\sigma_S(\mathbf{r})}{4\pi} \int_{\mathbb{S}^2} \psi(\mathbf{r}, \boldsymbol{\Omega}') \, d\boldsymbol{\Omega}' + Q(\mathbf{r})$$

with $\mathbf{r} \in V \subset \mathbb{R}^3$ and $\boldsymbol{\Omega} \in \mathbb{S}^2$. The argument $\psi(\mathbf{r}, \boldsymbol{\Omega})$ is called the **neutron flux**.

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with $\mathbf{r} \in V \subset \mathbb{R}^3$ and $\Omega \in \mathbb{S}^2$. The argument $\psi(\mathbf{r}, \Omega)$ is called the **neutron flux**. Boundary conditions

$$\psi(\mathbf{r}, \Omega) = 0, \quad \text{when} \quad n(\mathbf{r}) \cdot \Omega < 0, \quad \mathbf{r} \in \delta V.$$

Note: σ_T , σ_S and σ_A are called **cross-sections**. They are all strictly positive and satisfy $\sigma_T = \sigma_S + \sigma_A$

Source Iteration (described via operator notation)

Introduce

$$\mathcal{T}(\cdot) \equiv \Omega \cdot \nabla(\cdot) + \sigma_T(\mathbf{r})(\cdot) \quad \text{and define} \quad \phi(\mathbf{r}) = \frac{1}{4\pi} \int_{\mathbb{S}^2} \psi(\mathbf{r}, \Omega) \, d\Omega$$

ϕ is called the **scalar flux**. The transport equation is then

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Source Iteration (SI) is defined as follows

$$\begin{aligned} \mathcal{T}\psi^{(k+1)} &= \sigma_S\phi^{(k)} + Q \\ \phi^{(k+1)} &= \frac{1}{4\pi} \int_{\mathbb{S}^2} \psi^{(k+1)} \, d\Omega \end{aligned}$$

This basic iterative method is known to converge since

$$\|\sigma_S/\sigma_T\|_{\infty} < 1$$

Diffusion Approximation

Limitation of source iteration:

Potentially slow convergence when $\|\sigma_S/\sigma_T\|_\infty \approx 1$

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One approach:

Approximate ϕ (the scalar flux) using a diffusion equation.

$$-\nabla \cdot \left(\frac{1}{3\sigma_T(\mathbf{r})} \nabla \Theta(\mathbf{r}) \right) + \sigma_A(\mathbf{r})\Theta(\mathbf{r}) = Q(\mathbf{r}),$$

subject to

$$\Theta(\mathbf{r}) + \lambda n(\mathbf{r}) \cdot \nabla \Theta(\mathbf{r}) = 0, \quad \text{when } \mathbf{r} \in \delta V,$$

with λ a known constant.

Using asymptotics: $\Theta = \phi + \mathcal{O}(\epsilon^2)$, where ϵ is an asymptotic parameter.

Diffusion Synthetic Acceleration (DSA)

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Synthetic acceleration methods were first suggested by Kopp in 1963. DSA is such a method.

2-step process:

1. Do one step of source iteration,
2. use the diffusion approximation to estimate the error in step 1.

DSA: The Good and the Bad

Good:

DSA improves upon or maintains the convergence of source iteration for all values of σ_S/σ_T

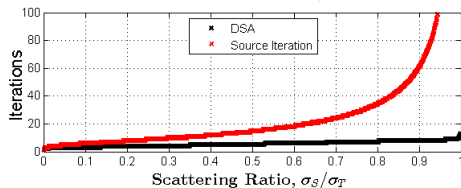


Figure: Iterations to converge to a tolerance of 10^{-6}

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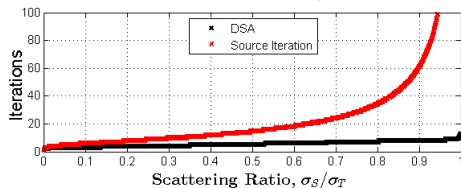


Figure: Iterations to converge to a tolerance of 10^{-6}

Bad:

- ▶ Discontinuous cross-sections can lead to degraded effectiveness of multidimensional DSA (Azmy, 1998, Warsa et. al., 2004).
- ▶ Higher computational cost per iteration.

Domain Decomposition approaches

Idea: separate the domain into *diffusive* and *non-diffusive* regions.

Diffusive → apply DSA

Non-diffusive → apply SI

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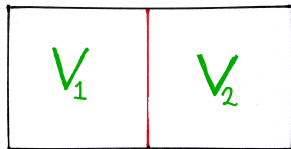
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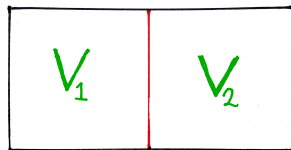
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Boundary conditions:

- ▶ Zero incoming flux on the external boundary,
- ▶ **Internal boundary?**

In general: use the flux on V_1 to impose internal conditions for V_2 ,
use the flux on V_2 to impose internal conditions for V_1 .

Two Domain Decomposition approaches

DDSI \equiv Domain Decomposed Source Iteration

Jacobi DDSI:

Internal boundary conditions for each subdomain are imposed using the **previous** iteration on neighbouring subdomains.

Gauss-Seidel DDSI:

Internal boundary conditions for each subdomain are imposed using the **current** iteration on neighbouring subdomains.

Proved: Gauss-Seidel DDSI \equiv Source Iteration

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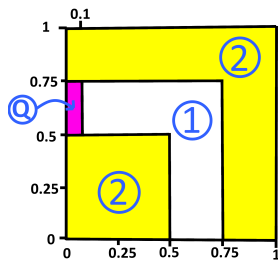
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Algorithm:	Parallelisation Potential	Rate of convergence	Arbitrary subdomain shapes
Jacobi DDSI	Angle & space	Slower than SI	✓
Gauss-Seidel DDSI	Angle only	Same as SI	✗

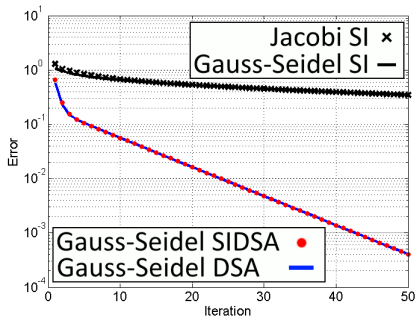
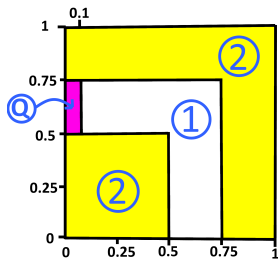
Numerical Results

(1): Diffusive
(2), (Q): Non-diffusive



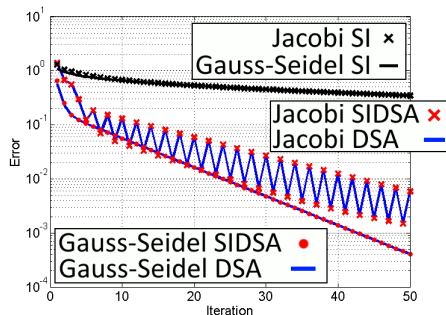
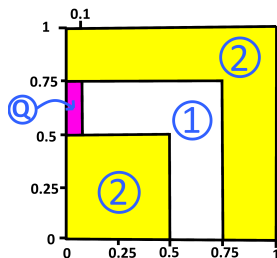
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Method	Time
Jacobi SI	758
Gauss-Seidel SI	748
Jacobi DSA	2155
Gauss-Seidel DSA	2028
Jacobi SIDSA	1182
Gauss-Seidel SIDSA	1123