

Introduction to Simulation - Lecture 23

Fast Methods for Integral Equations

Jacob White

Thanks to Deepak Ramaswamy, Michal Rewienski,
and Karen Veroy

Outline

Solving Discretized Integral Equations

Using Krylov Subspace Methods

Fast Matrix-Vector Products

Multipole Algorithms

Multipole Representation.

Basic Hierarchy

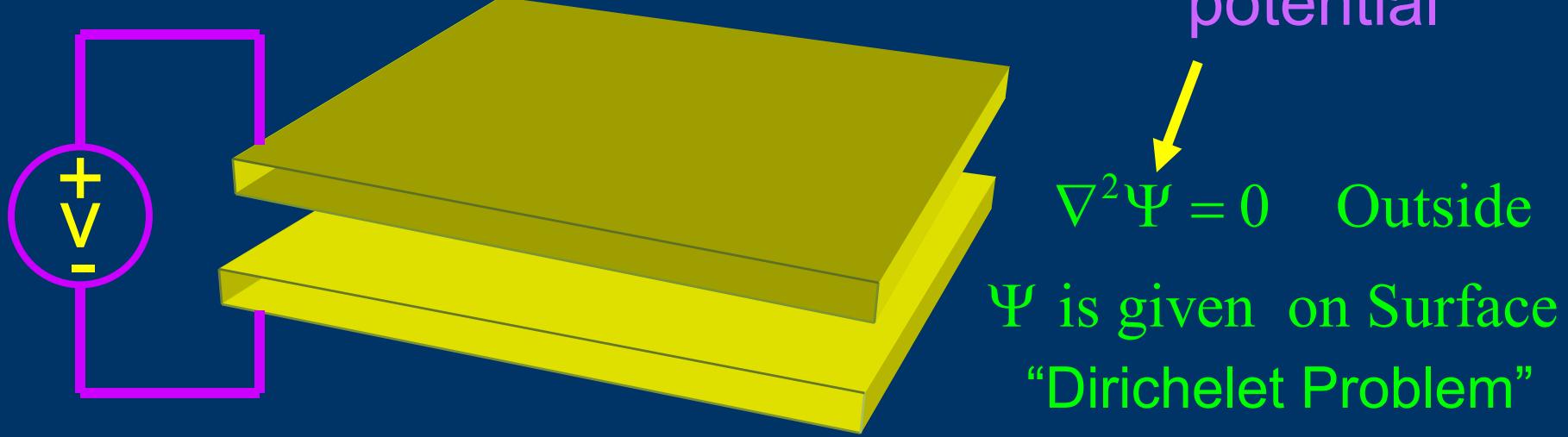
Algorithmic Improvements

Local Expansions

Adaptive Algorithms

Computational Results

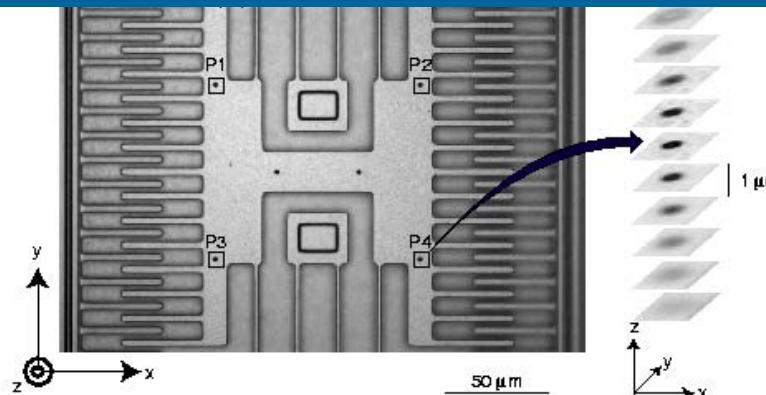
Exterior Problem in Electrostatics



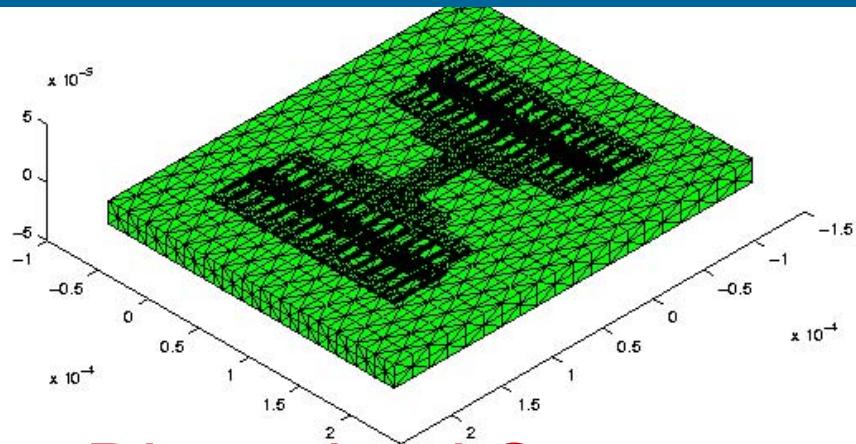
First Kind Integral Equation For Charge:

$$\Psi(x) = \int_{surface} \frac{1}{\|x - x'\|} \underbrace{\sigma(x')}_{\substack{\text{Charge} \\ \text{Green's Function}}} dS'$$

Drag Force in a Microresonator

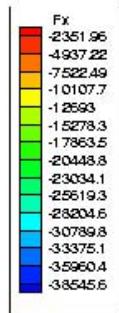


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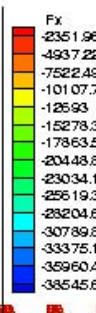
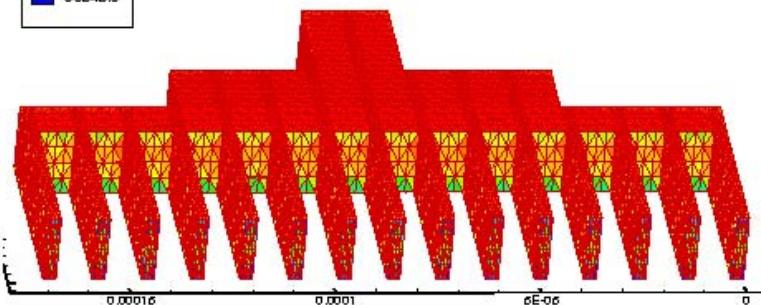


Resonator

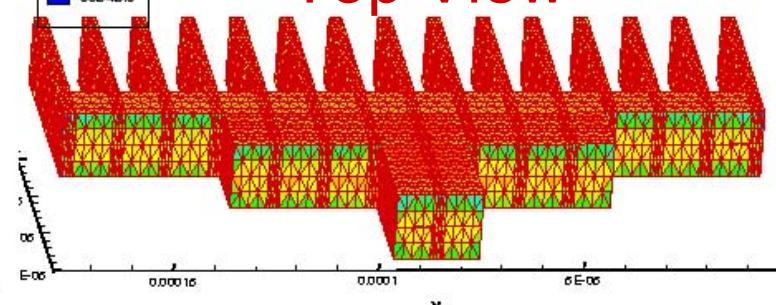
Discretized Structure



Computed Forces Bottom View



Computed Forces Top View



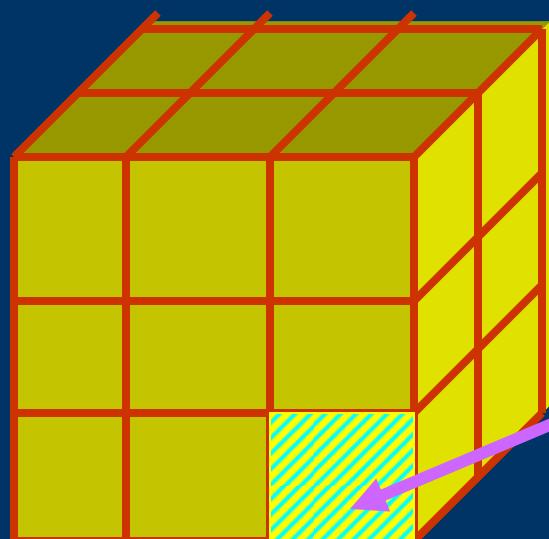
3-D Laplace's Equation

Basis Function Approach

Piecewise Constant Basis

Integral Equation: $\Psi(x) = \int_{surface} \frac{1}{\|x - x'\|} \sigma(x') dS'$

Discretize Surface into
Panels



Represent $\sigma(x) \approx \sum_{i=1}^n \alpha_i \underbrace{\varphi_i(x)}_{\text{Basis Functions}}$

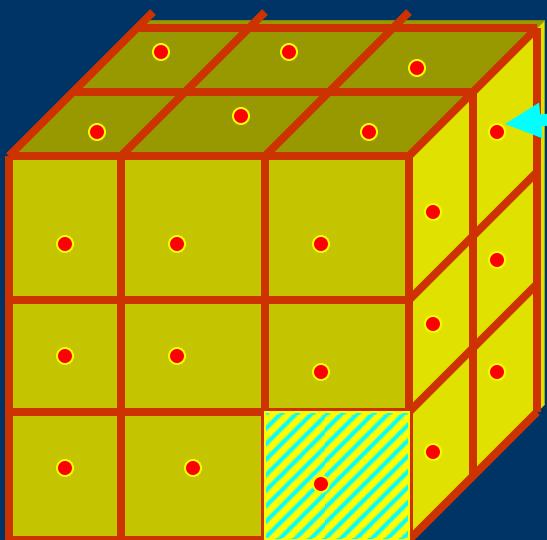
Panel j $\varphi_j(x) = 1 \quad \text{if } x \text{ is on panel j}$
 $\varphi_j(x) = 0 \quad \text{otherwise}$

3-D Laplace's Equation

Basis Function Approach

Centroid Collocation

Put collocation points at panel centroids



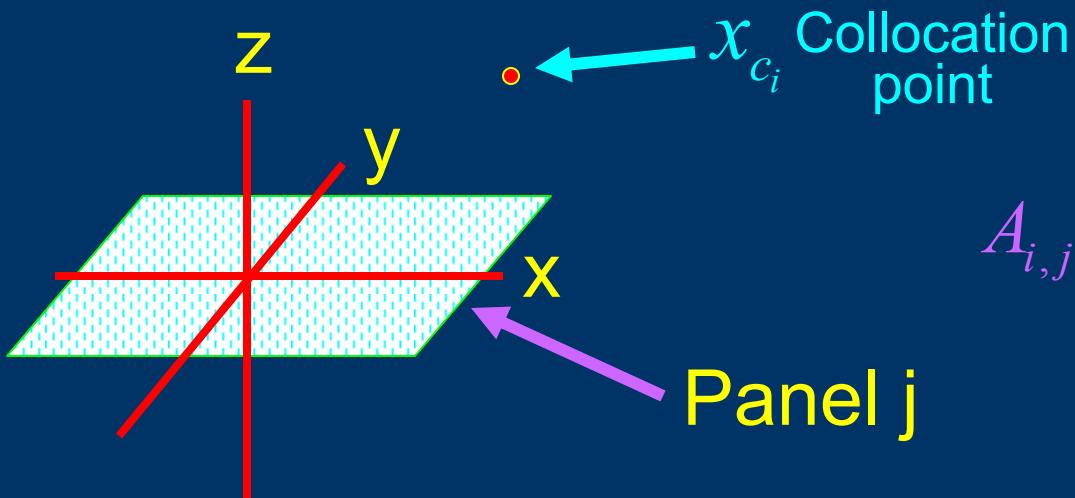
$$\Psi(x_{c_i}) = \sum_{j=1}^n \alpha_j \underbrace{\int_{\text{panel } j} G(x_{c_i}, x') dS'}_{A_{i,j}}$$

$$\begin{bmatrix} A_{1,1} & \cdots & \cdots & A_{1,n} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ A_{n,1} & \cdots & \cdots & A_{n,n} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \Psi(x_{c_1}) \\ \vdots \\ \vdots \\ \Psi(x_{c_n}) \end{bmatrix}$$

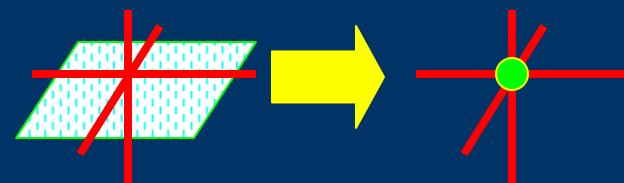
3-D Laplace's Equation

Basis Function Approach

Calculating Matrix Elements

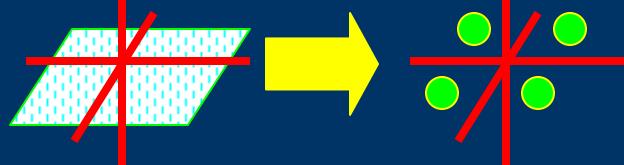


One point
quadrature
Approximation



$$A_{i,j} = \int_{\text{panel } j} \frac{1}{\|x_{c_i} - x'\|} dS'$$

Four point
quadrature
Approximation



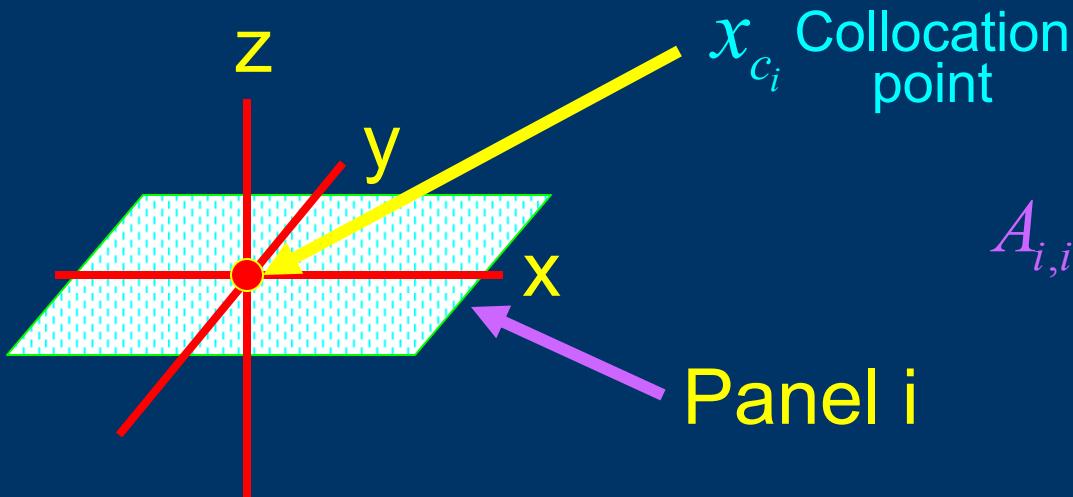
$$A_{i,j} \approx \frac{\text{Panel Area}}{\|x_{c_i} - x_{\text{centroid}_j}\|}$$

$$A_{i,j} \approx \sum_{j=1}^4 \frac{0.25 * \text{Area}}{\|x_{c_i} - x_{\text{point}_j}\|}$$

3-D Laplace's Equation

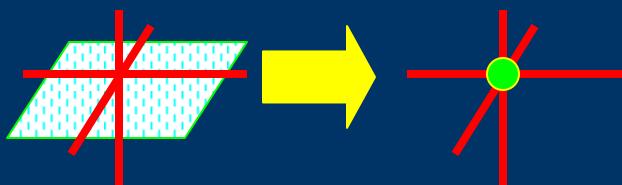
Basis Function Approach

Calculating “Self-Term”



$$A_{i,i} = \int_{\text{panel } i} \frac{1}{\|x_{c_i} - x'\|} dS'$$

One point
quadrature
Approximation



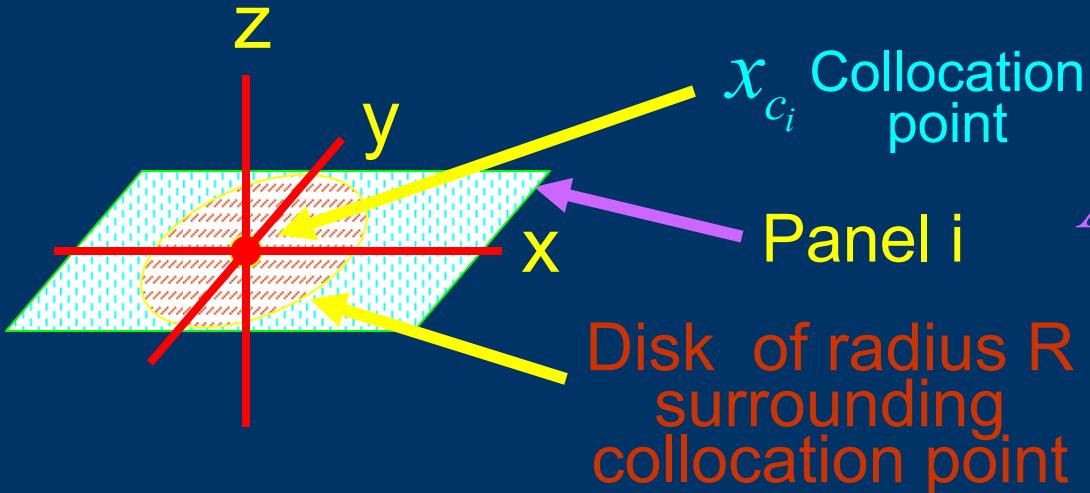
$$A_{i,i} \approx \frac{\text{Panel Area}}{\|x_{c_i} - x_{c_i}\|}$$

$$A_{i,i} = \int_{\text{panel } i} \frac{1}{\|x_{c_i} - x'\|} dS' \text{ is an integrable singularity}$$

3-D Laplace's Equation

Basis Function Approach

Calculating “Self-Term”
Tricks of the trade



$$A_{i,i} = \int_{\text{panel } i} \frac{1}{\|x_{c_i} - x'\|} dS'$$

Integrate in two pieces

$$A_{i,i} = \int_{\text{disk}} \frac{1}{\|x_{c_i} - x'\|} dS' + \int_{\text{rest of panel}} \frac{1}{\|x_{c_i} - x'\|} dS'$$

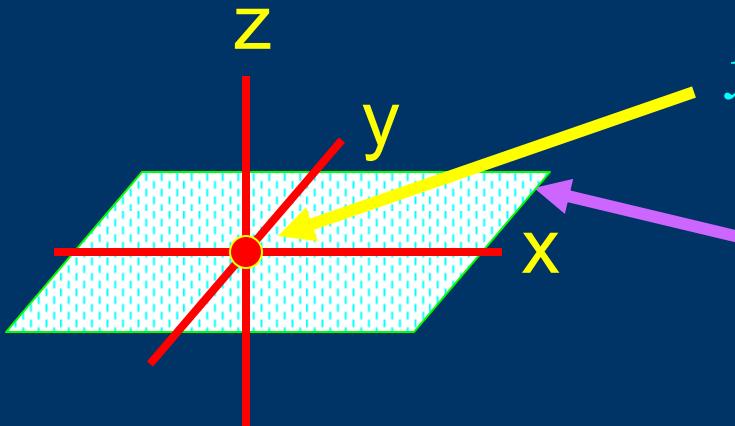
Disk Integral has singularity but has analytic formula

$$\int_{\text{disk}} \frac{1}{\|x_{c_i} - x'\|} dS' = \int_0^R \int_0^{2\pi} \frac{1}{r} r dr d\theta = 2\pi R$$

3-D Laplace's Equation

Basis Function Approach

Calculating “Self-Term”
Other Tricks of the trade



$$A_{i,i} = \int_{\text{panel } i} \frac{1}{\|x_{c_i} - x'\|} dS'$$

Integrand is singular

- 1) If panel is a flat polygon, analytical formulas exist
- 2) Curve panels can be handled with projection

3-D Laplace's Equation

Basis Function Approach

Galerkin (test=basis)

$$\underbrace{\int \varphi_i(x) \Psi(x) dS}_{b_i} = \sum_{j=1}^n \alpha_j \underbrace{\iint \varphi_i(x) G(x, x') \varphi_j(x') dS' dS}_{A_{i,j}}$$

For piecewise constant Basis

$$\underbrace{\int \Psi(x) dS'}_{b_i} = \sum_{j=1}^n \alpha_j \underbrace{\int_{\text{panel } i} \int_{\text{panel } j} \frac{1}{\|x - x'\|} dS' dS}_{A_{i,j}}$$

$$\begin{bmatrix} A_{1,1} & \cdots & \cdots & A_{1,n} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ A_{n,1} & \cdots & \cdots & A_{n,n} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ \vdots \\ b_n \end{bmatrix}$$

Integral Equation Method Generate Huge Dense Matrices

$$\begin{bmatrix} A_{1,1} & \cdots & \cdots & A_{1,n} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ A_{n,1} & \cdots & \cdots & A_{n,n} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \Psi(x_{c_1}) \\ \vdots \\ \vdots \\ \Psi(x_{c_n}) \end{bmatrix}$$

Gaussian Elimination Much Too Slow!

Solving Discretized Integral Equations

The Generalized Conjugate Residual Algorithm

The kth step of GCR

compute Ap_k

$$\alpha_k = \frac{(r^k)^T (Ap_k)}{(Ap_k)^T (Ap_k)}$$

$$x^{k+1} = x^k + \alpha_k p_k$$

$$r^{k+1} = r^k - \alpha_k Ap_k$$

$$p_{k+1} = r^{k+1} - \sum_{j=0}^k \frac{(Ar^{k+1})^T (Ap_j)}{(Ap_j)^T (Ap_j)} p_j$$

For discretized Integral equations, A is dense

Determine optimal stepsize in kth search direction

Update the solution and the residual

Compute the new orthogonalized search direction

Solving Discretized Integral Equations

The Generalized Conjugate Residual Algorithm

Complexity of GCR

compute Ap_k

$$\alpha_k = \frac{(r^k)^T (Ap_k)}{(Ap_k)^T (Ap_k)}$$

$$\begin{aligned}x^{k+1} &= x^k + \alpha_k p_k \\r^{k+1} &= r^k - \alpha_k Ap_k\end{aligned}$$

$$p_{k+1} = r^{k+1} - \sum_{j=0}^k \frac{(Ar^{k+1})^T (Ap_j)}{(Ap_j)^T (Ap_j)} p_j$$

Dense Matrix-vector product costs $O(n^2)$

Vector inner products, $O(n)$

Vector Adds, $O(n)$

$O(k)$ inner products,
total cost $O(nk)$

Algorithm is $O(n^2)$ for Integral Equations
even though # iters (k) is small!

Solving Discretized Integral Equations

The Generalized Conjugate Residual Algorithm

Fast Matrix Vector Products

exactly compute Ap_k

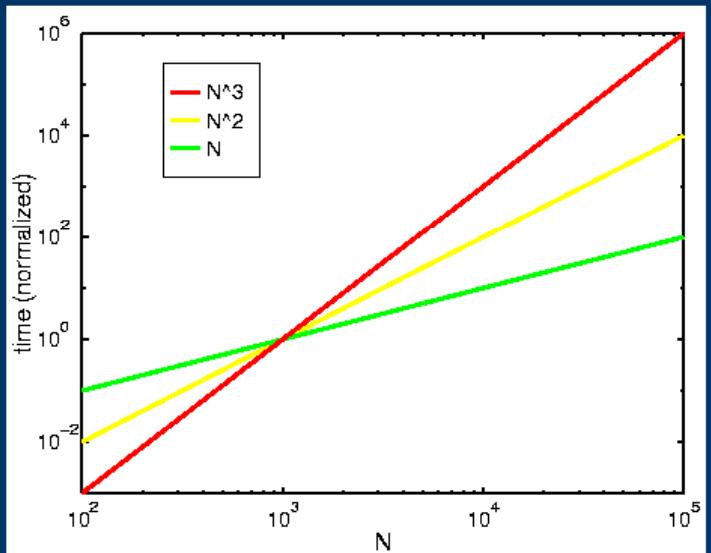
Dense Matrix-vector product costs $O(n^2)$

approximately compute Ap_k

Reduces Matrix-vector product costs to
 $O(n)$ or $O(n \log n)$

Computational Costs

Fast Solvers



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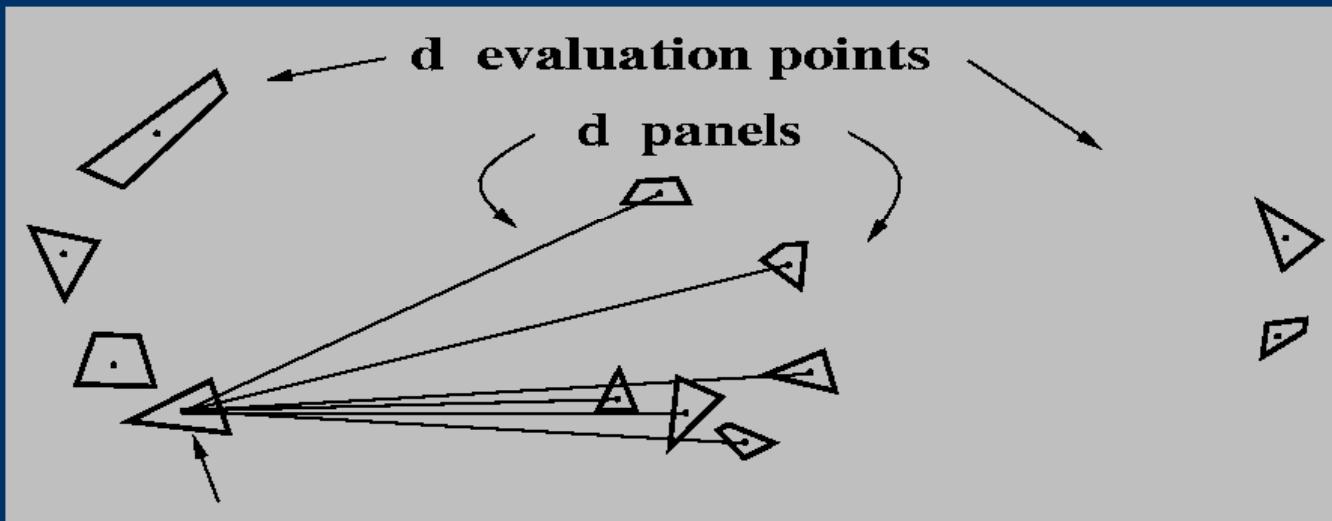
N	Gaussian Elim	"Fast" $O(N)$
	300 MFLOPS	30 MFLOPS
5e4	3 days, 20GB	80sec, 130M
1e5	25 days, 80GB	2.5min, 300M
5e5	8.8yrs, 2TB	15min, 1.5GB

- Gaussian Elimination: $O(n^3)$ time, $O(n^2)$ memory
- GCR with direct M-V: $O(n^2)$ time, $O(n^2)$ memory
- Fast Methods: $O(n)$ time, $O(n)$ memory

Basic Multipole Concepts

Multipole Representation

Direct Potential Evaluation



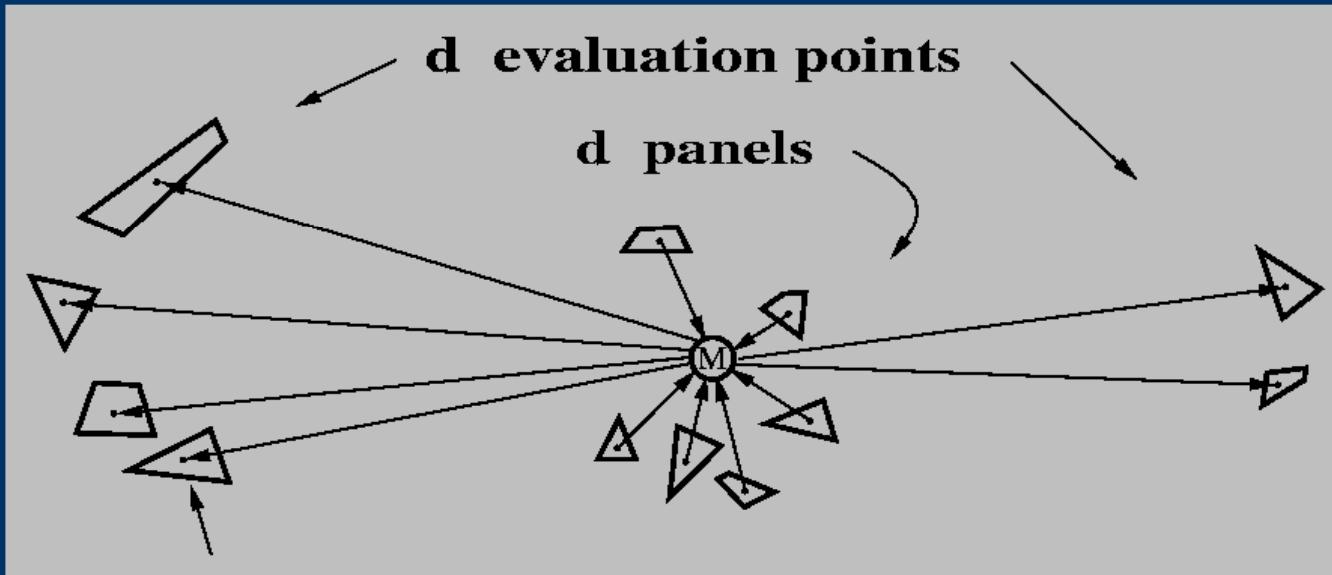
N1

- Potential at point i : $v_i(r_i, \phi_i, \theta_i) = \sum_{j=1}^d q_j P_{ij}$.
- Complete evaluation at d points costs d^2 operations.

Basic Multipole Concepts

Multipole Representation

Multipole Potential Evaluation



N2

- Approximate potential at point i :

$$v_i(r_i, \phi_i, \theta_i) \approx \sum_{j=0}^{\text{order}} \sum_{k=-j}^j \frac{M_j^k}{r_i^{j+1}} Y_j^k(\phi_i, \theta_i).$$

Basic Multipole Concepts

Multipole Representation

...Multipole Potential Evaluation

- Multipole coefficients function of panel charges:

$$M_j^k \triangleq \sum_{i=1}^d \frac{q_i}{A_i} \int_{\text{panel } i} \rho^j Y_j^{-k}(\alpha, \beta) dA.$$

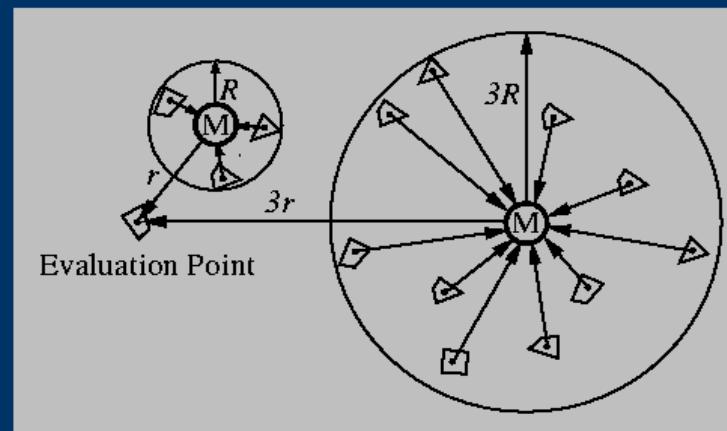
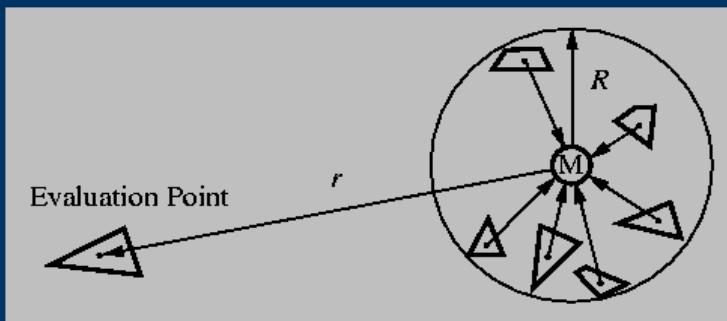
- Computing Multipole expansions costs order d operations.
- Each approximate potential evaluation costs order 1 operations.

d potential evaluation due to d panels in order d operations

Basic Multipole Concepts

Multipole Representation

Scale Invariance of Error



$$\text{Error} \leq K \left(\frac{R}{r} \right)^{\text{order}+1}$$

$$\text{Error} \leq K \left(\frac{3R}{3r} \right)^{\text{order}+1}$$

Basic Multipole Concepts

Multipole Representation

Multipole Algorithm Hierarchy

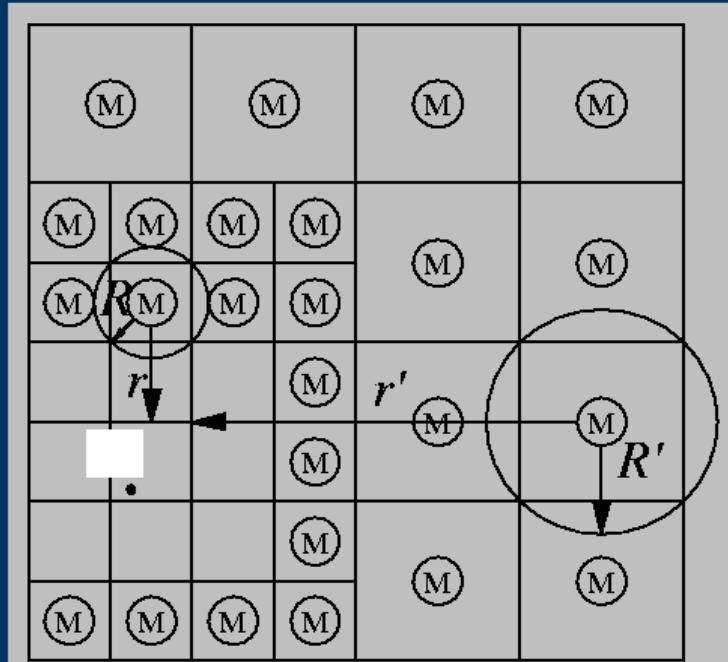
Hierarchy guarantees:

- Bounded error:

$$\text{Error} \leq K \left(\frac{\mathbf{R}}{r} \right)^{\text{order}+1}$$

$$\leq K \left(\frac{1}{2} \right)^{\text{order}+1}$$

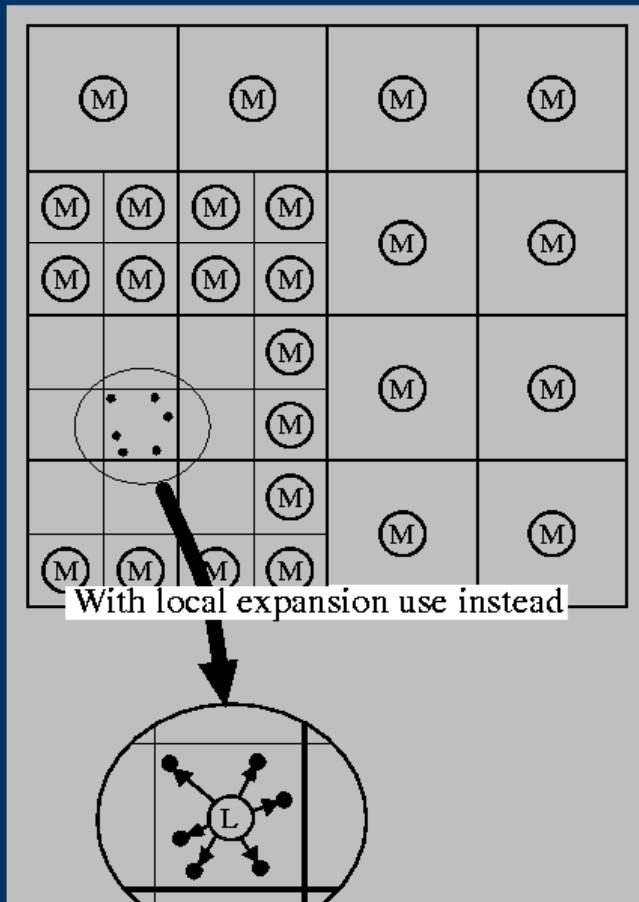
$\text{order} = 2$ yields one percent accuracy.



Multipole Optimizations

Local Expansions

Cost Reduction

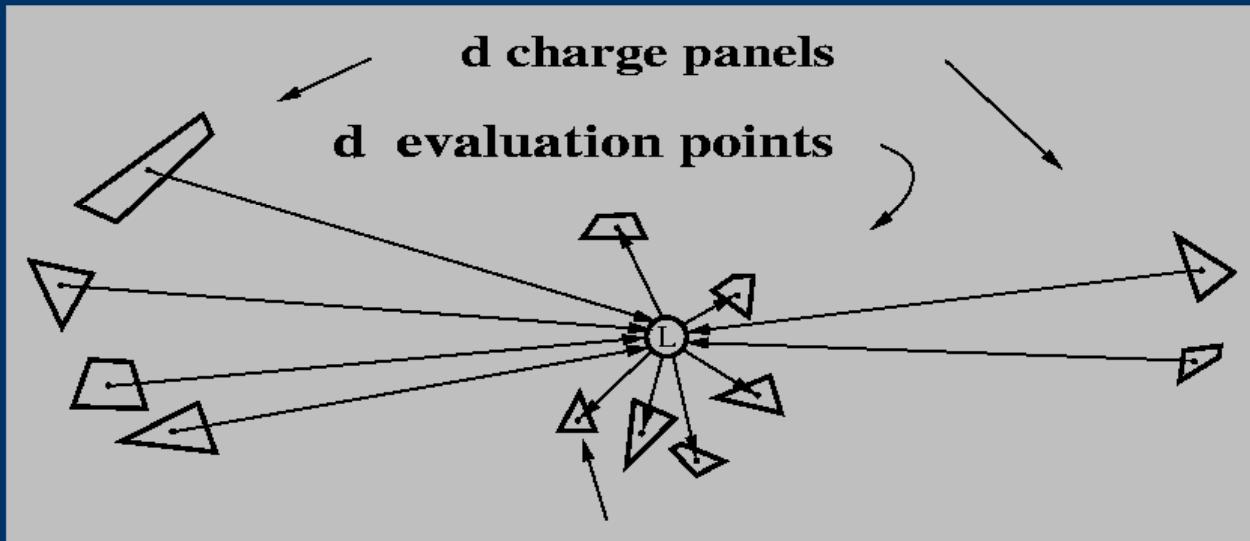


- Construct a local expansion to represent distant charge potentials.
- Evaluate a single local expansion, rather than many multipole expansions, at each evaluation point.

Multipole Optimizations

Local Expansions

Clustered Evaluations



N3

- Local expansion summarizes the influence of distant charge for clusters of evaluation points.

Multipole Optimizations

Local Expansions

...Clustered Evaluations

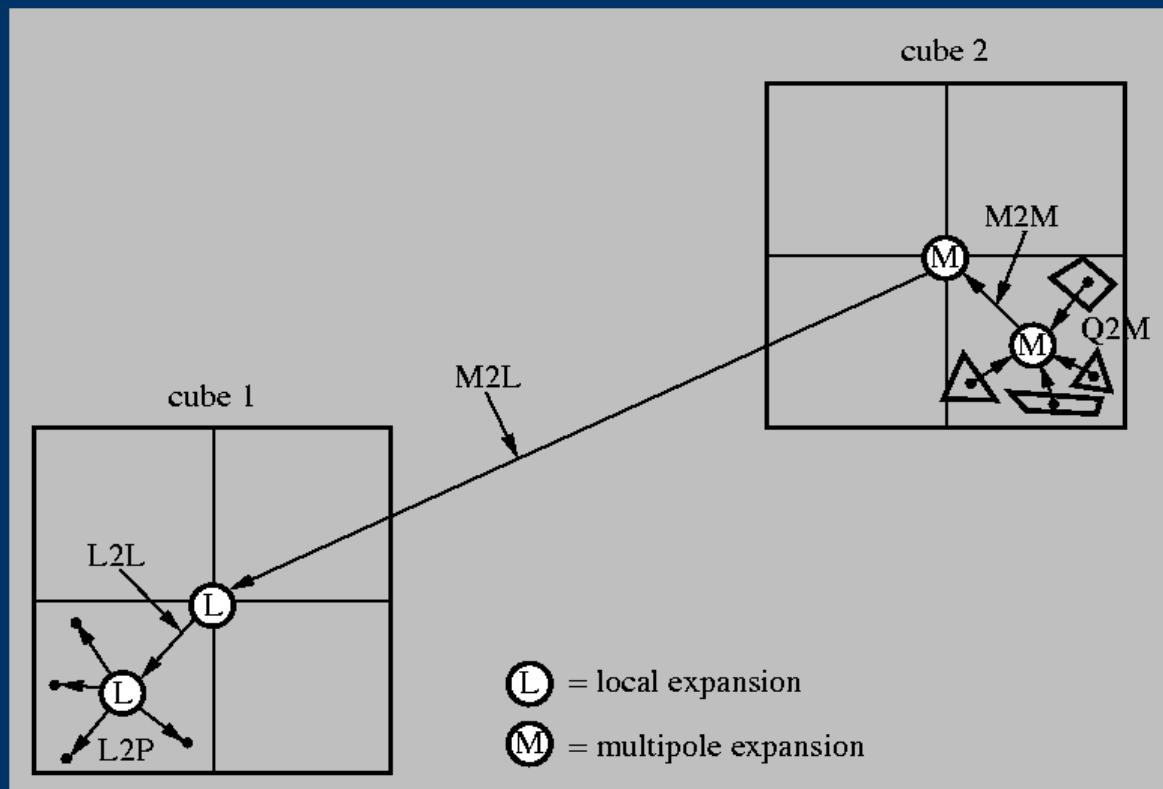
- Gives $O(n)$ potential evaluation when combined with coalescing of charge done by multipole expansions.
- Approximate potential at point i :

$$v_i(r_i, \phi_i, \theta_i) \approx \sum_{j=0}^{\text{order}} \sum_{k=-j}^j L_j^k Y_j^k(\phi_i, \theta_i) r_i^j.$$

Multipole Optimizations

Local Expansions

Summary of Operations



N4

Multipole Optimizations

Local Expansions

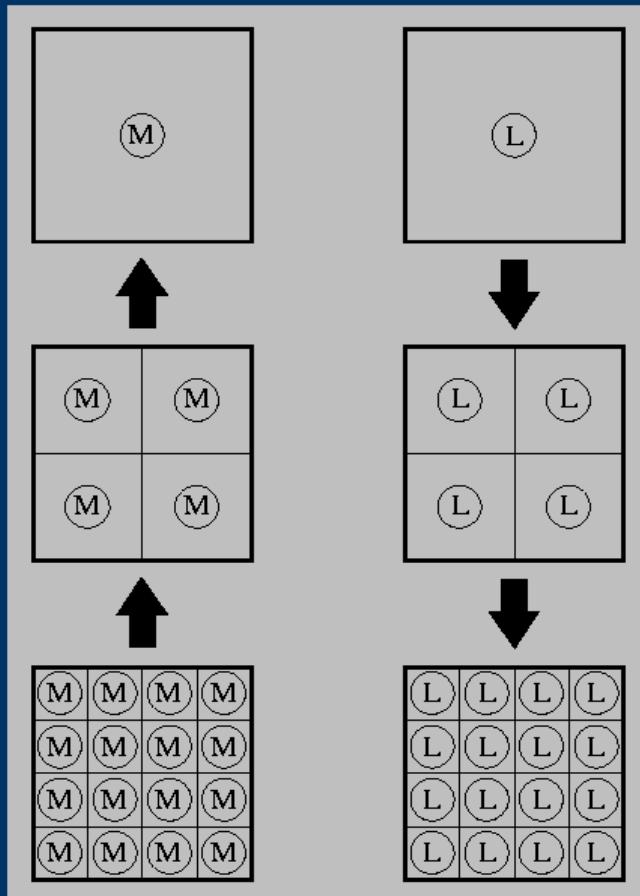
...Summary of Operations

- Multipole and local expansions are built using complementary hierarchies.
- Complete calculation consists of:
 1. Build multipoles (Upward Pass).
 2. Build locals (Downward Pass).
 3. Evaluate local expansions and nearby charge potential (Evaluation Pass).

Multipole Optimizations

Local Expansions

Hierarchy Construction

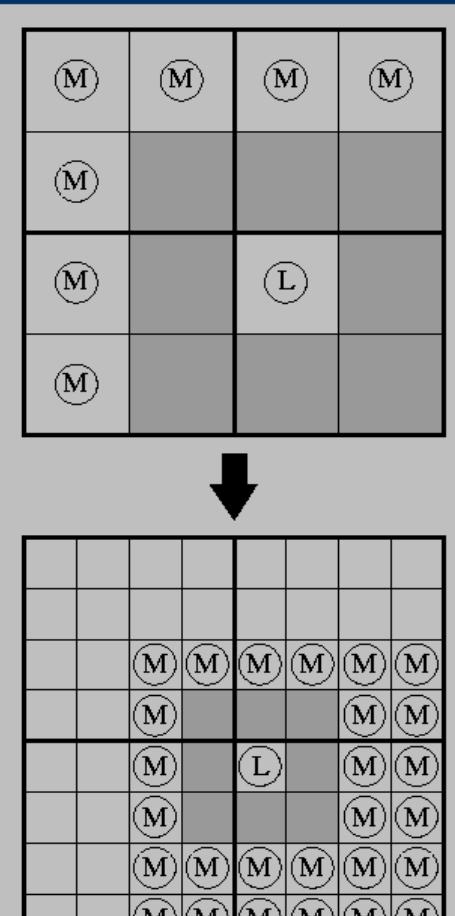


- First build the multipole expansions moving upward from child to parent.
- Then build the local expansions by moving downward from parent to child.
- Computation has a tree structure.

Multipole Optimizations

Local Expansions

Construction Details



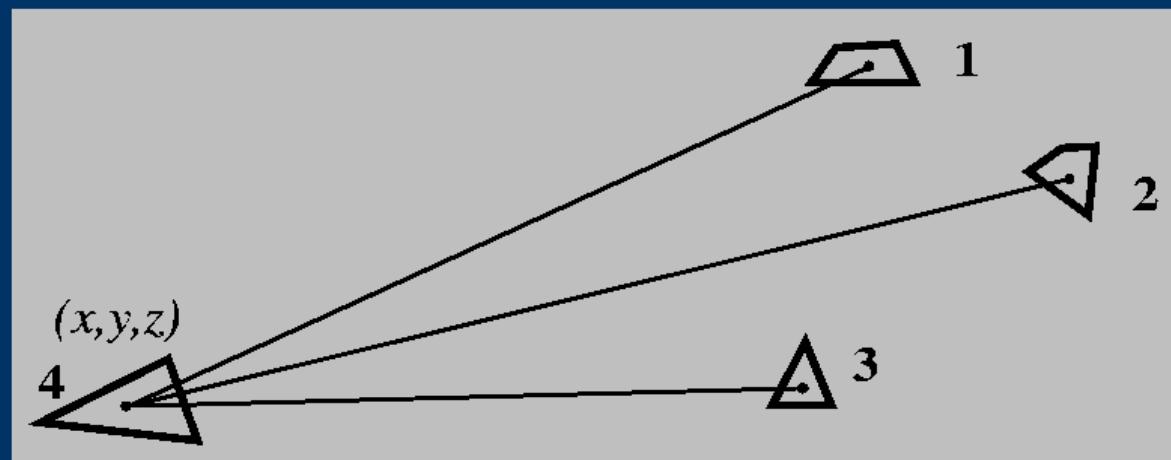
- Conversion of multipole expansions to local expansions.
- A child's local expansion is its parents local expansion plus conversions of multipole expansions in child's interaction range.

Multipole Optimizations

Adaptive Algorithm

Multipole Inefficiency

Direct Evaluation



N5

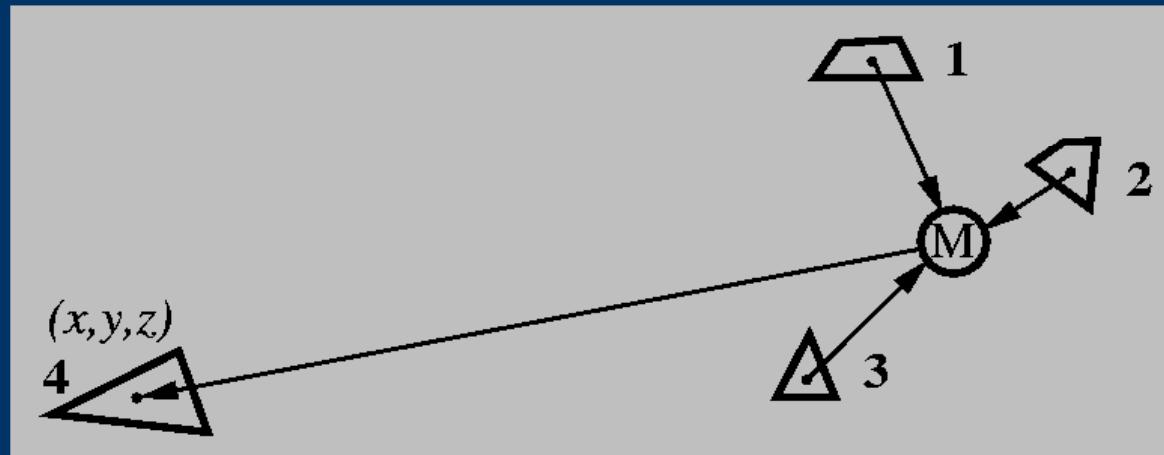
$$v_4(x, y, z) = q_1 P_{41} + q_2 P_{42} + q_3 P_{43}$$

Multipole Optimizations

Adaptive Algorithm

...Multipole Inefficiency

Multipole Evaluation



N6

$$v_4(x, y, z) \approx \bar{M}_0^0 \frac{1}{r} + \bar{M}_1^0 \frac{z}{r^3} - \bar{M}_1^1 \frac{x}{2r^3} - \bar{M}_1^1 \frac{y}{2r^3}$$

Using Multipole MORE expensive than Direct.

Multipole Optimizations

Adaptive Algorithm

Simple Adaptive Scheme

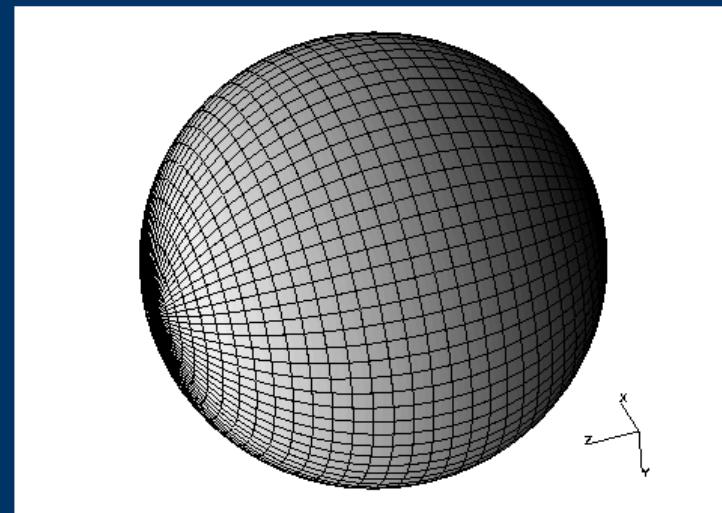
If there are fewer panels than multipole coefficients, calculate the panels' influence directly.

- Similarly, local expansions are not used if there are fewer evaluation points than local expansion coefficients.
- Retains $O(mn)$ complexity for nonuniform panel distributions.

Computational Examples

Translating Sphere

Potential Distribution

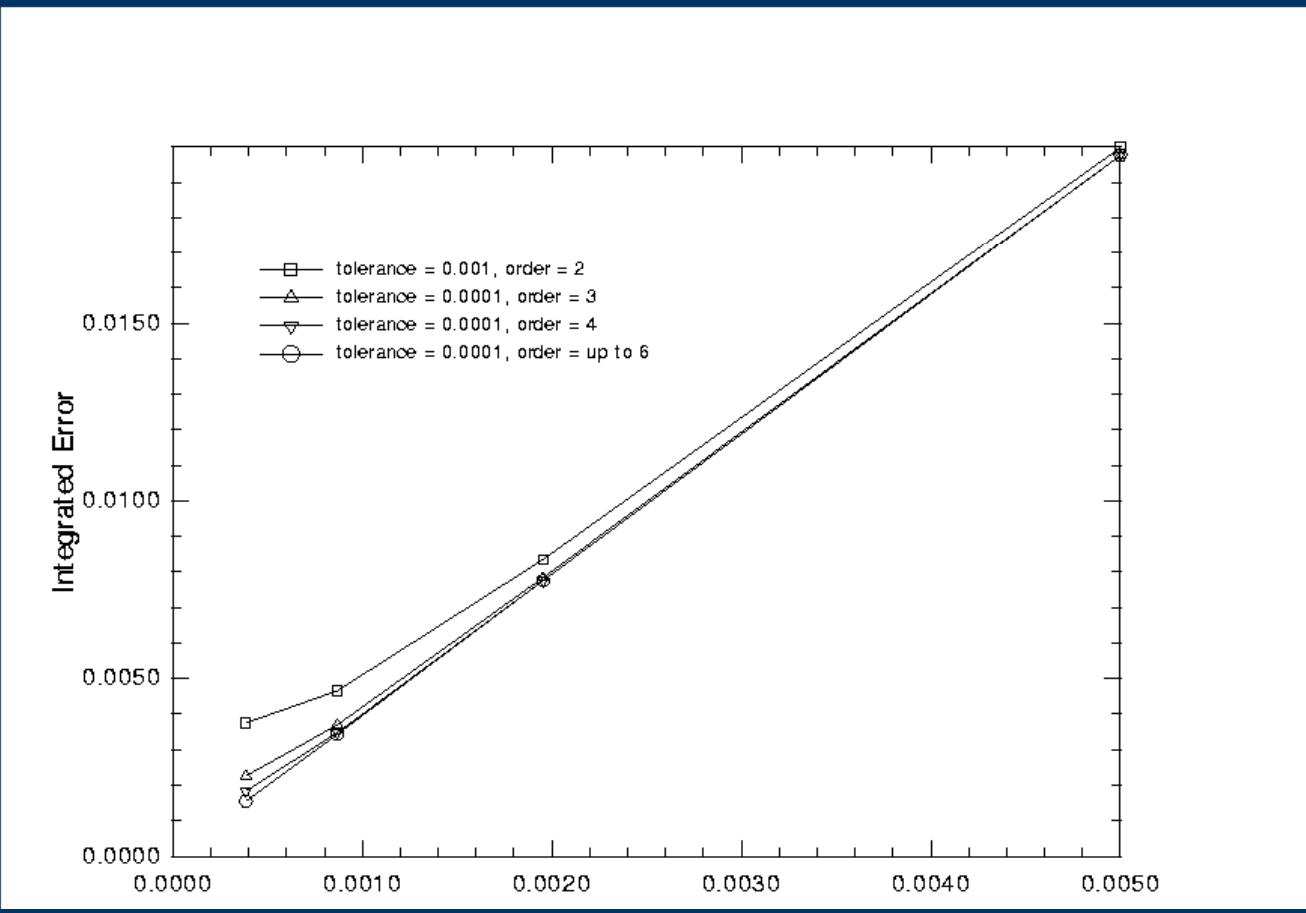


- Potential given by $\psi(x) = -\frac{x_3}{2\|x\|^3}$.
- Charge given by $\sigma(x) = \frac{-3}{8\pi}x_3$.

Computational Examples

Translating Sphere

Discretization Convergence



Computational Examples

Translating Sphere

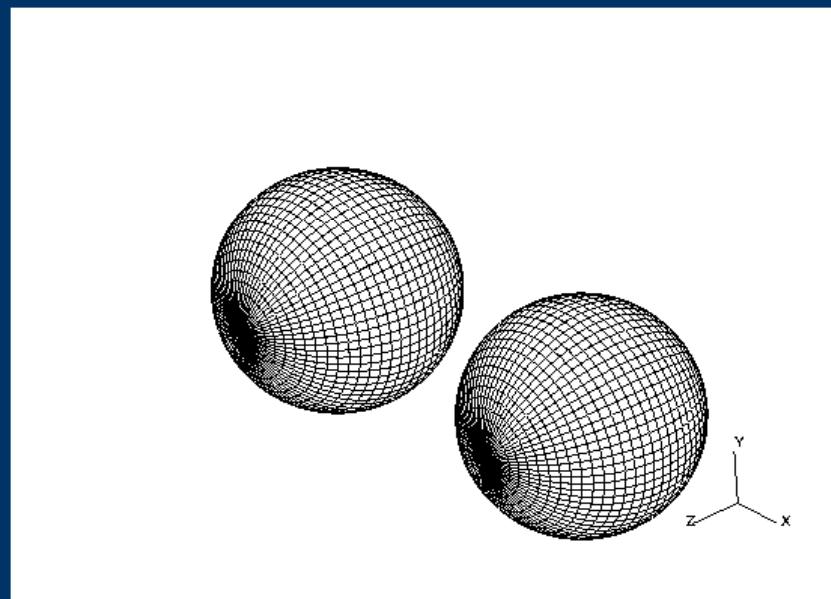
...Discretization Convergence

- Error should decay like $\frac{1}{n}$.
- Multipole approximations eventually interfere.
- Higher-order multipole expansions needed for higher accuracy.

Computational Examples

Two Sphere Example

Potential Distribution

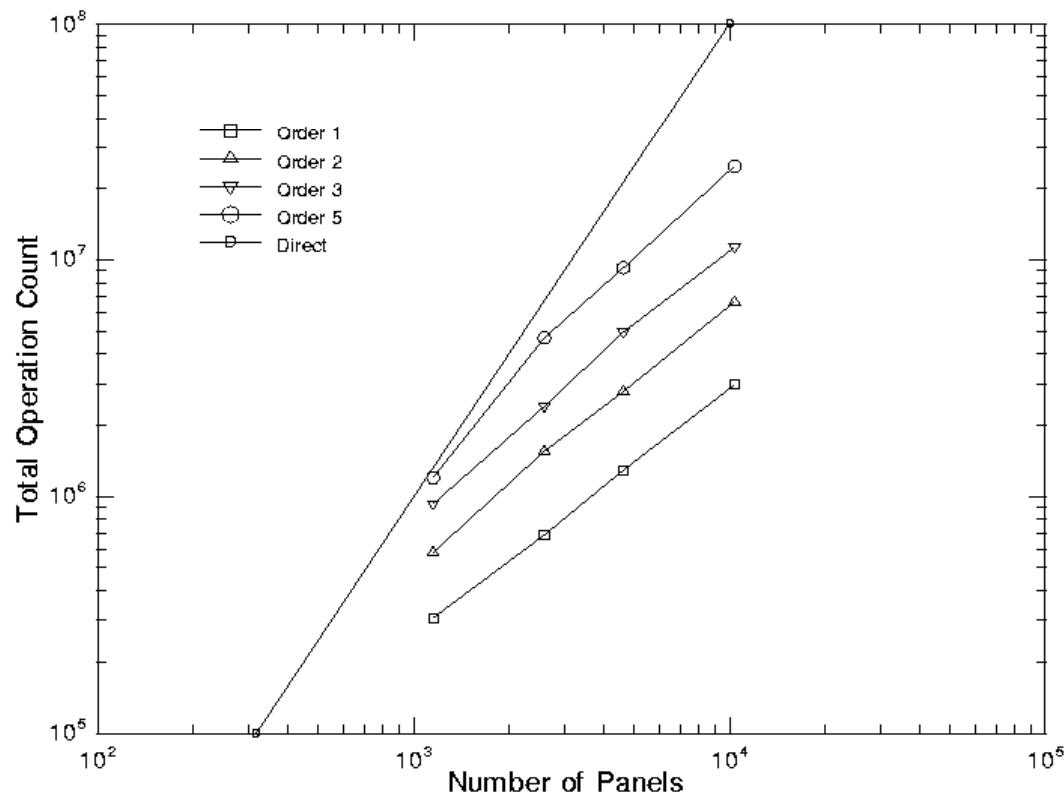


- Potential on each sphere: $\psi(\mathbf{x}) = -\frac{\mathbf{x}_3}{2\|\mathbf{x}\|^3}$.
- Does not correspond to a simple physical problem.

Computational Examples

Two Sphere Example

Matrix-Vector Product Cost



Computational Examples

Two Sphere Example

...Matrix-Vector Product Cost

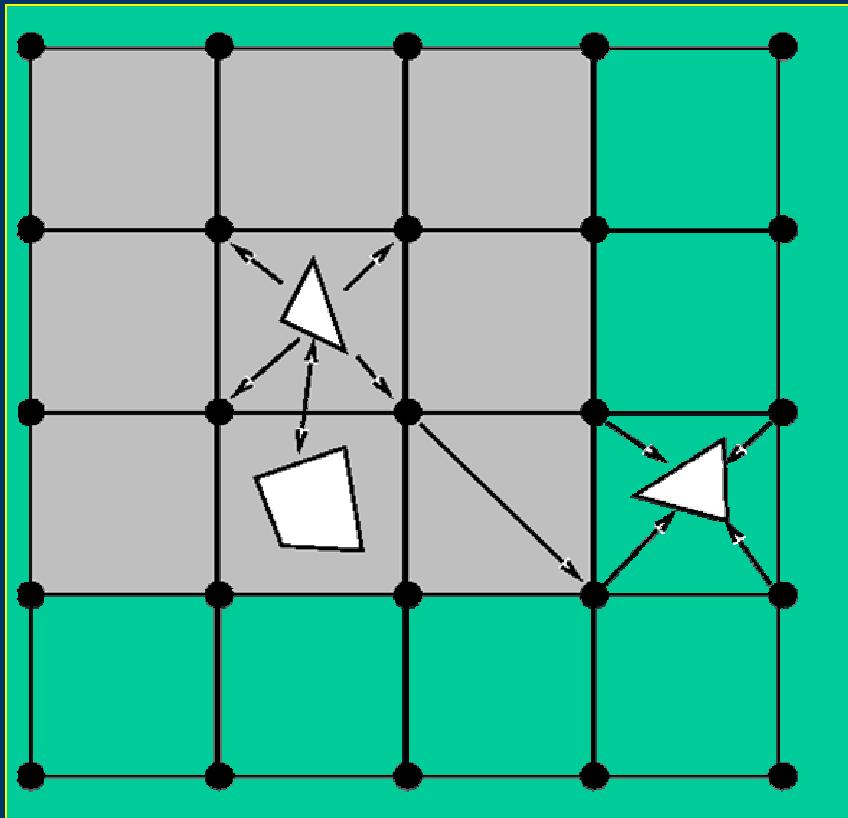
- Direct matrix-vector product cost increases like n^2 .
- Multipole matrix-vector product cost increases like n .
- The slope for the multipole algorithm depends on accuracy.
- For order 2 expansions, breakpoint is about $n = 400$.

Complexity Summary

For an integral equation discretized with n panels:

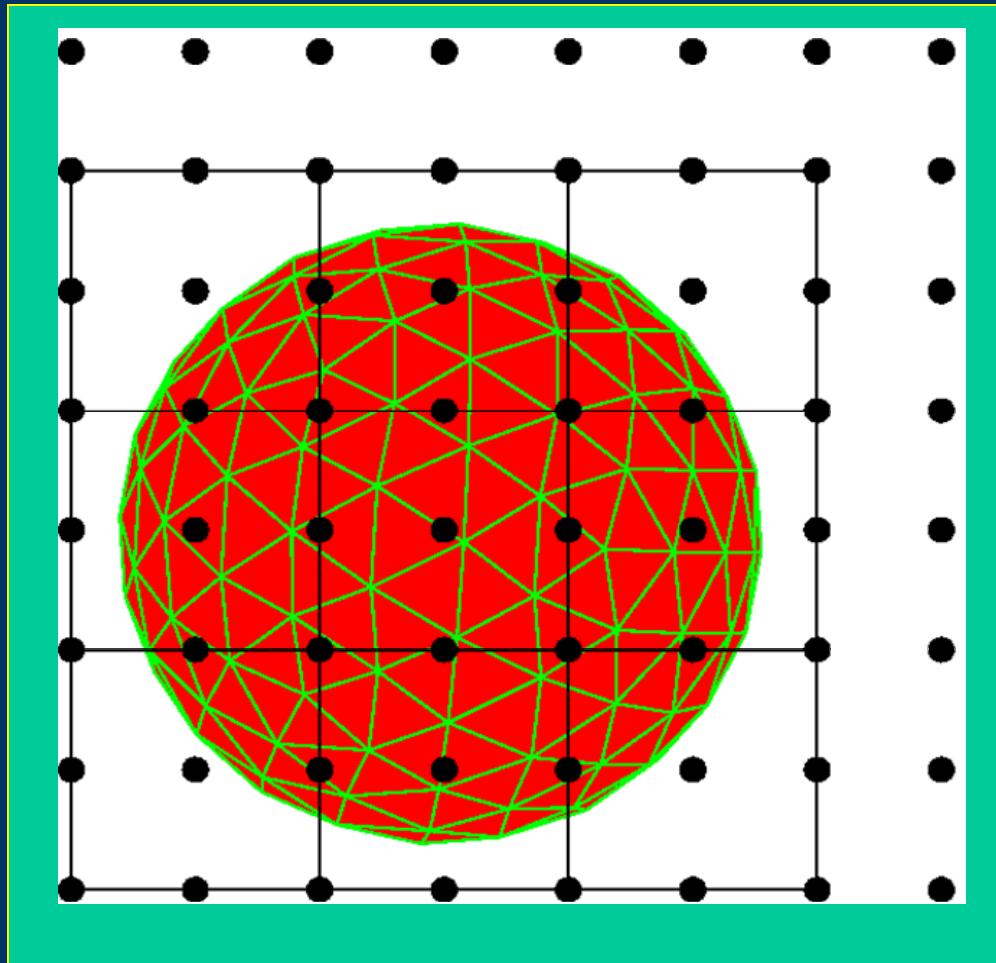
- Gaussian elimination: $O(n^3)$.
- GCR, direct M-V $O(n^2)$.
- Multipole accelerated GCR $O(mn)$.

Precorrected-FFT Acceleration



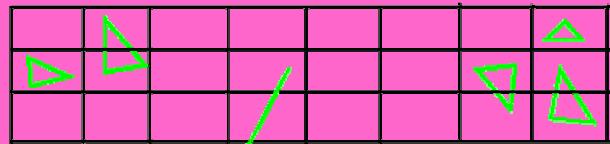
- Project panel charges on grid $q_g = Wq$.
- Compute using FFT's grid potentials due to grid charges $\psi_g = Hq_g$.
- Interpolate grid potentials onto panels $\psi = V\psi_g$.
- Compute near interactions directly $\psi_{a,b} = P_{a,b}q_b$.

The FFT Grid Selected To Balance Costs



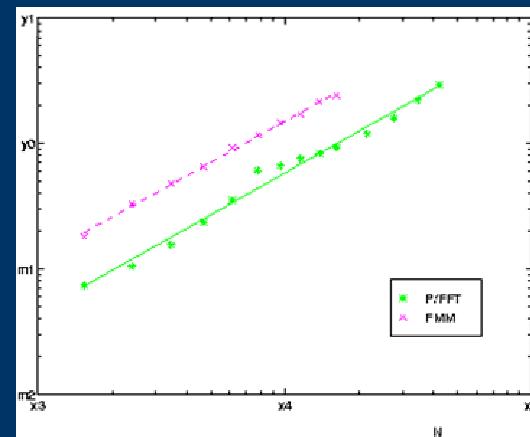
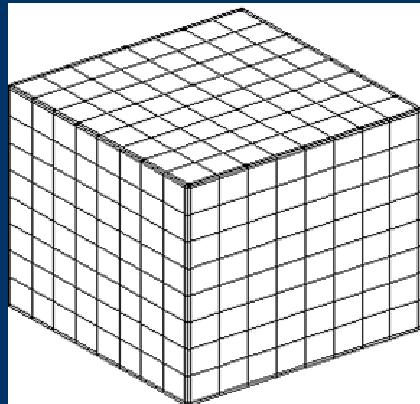
- Grid Selected So Direct Cost equals FFT Cost.
- Finer Problem Discretizations Usually Yield Finer Grids.

Inhomogeneity Problem



- Inhomogeneity - Empty Grid due to FFT - Inefficiency

Refining Cube Discretization - Worsening Inhomogeneity
MV Product Time



Summary

Solving Discretized Integral Equations
GCR plus Fast Matrix-Vector Products
Multipole Algorithms
 Multipole Representation.
 Basic Hierarchy
Algorithmic Improvements
 Local Expansions
 Adaptive Algorithms
Computational Results
Precorrected-FFT Algorithms