

Comparison of Geometric and Algebraic Multigrid for Data-Sparse Boundary Element Matrices

U. Langer¹

D. Pusch¹

¹Institute of Computational Mathematics
Johannes Kepler University Linz
{ulanger, pusch}@numa.uni-linz.ac.at

This work has been supported by the Austrian Science Fund 'Fonds zur Förderung der wissenschaftlichen Forschung (FWF)' under the grant 'Project P 14953 '

Outline of the Talk

- Preliminaries
- Boundary Element Method and Adaptive Cross Approximation
- Multigrid Methods
 - Geometric Multigrid
 - Algebraic Multigrid
- Convergence of the V-Cycle for ACA Matrices
- Numerical Results
- Conclusions

Problem Formulation

Let $\Omega \subset \mathbb{R}^d$ be a bounded Lipschitz domain and $\Gamma = \partial\Omega$.

1. Interior Dirichlet Problem:

$$\begin{aligned} -\Delta u &= 0 & x \in \Omega \\ u(x) &= g(x) & x \in \Gamma \end{aligned}$$

2. Representation Formula:

$$\sigma(y)u(y) = - \int_{\Gamma} u(x) \frac{\partial E}{\partial n_x}(x, y) ds_x + \int_{\Gamma} \frac{\partial u}{\partial n_x}(x) E(x, y) ds_x$$

$$\begin{aligned} \sigma(y) &= 0 & y \notin \bar{\Omega} \\ \sigma(y) &= \frac{\Theta}{2\pi} & y \in \Gamma \\ \sigma(y) &= 1 & y \in \Omega \end{aligned}$$

Problem Formulation

we obtain the compact operator-form:

$$Vv = \left(\frac{1}{2}I + K\right)u$$

V ... single layer potential operator

K ... double layer potential operator

u ... Dirichlet data

$v = \partial u / \partial n$... Neumann data

BEM - Sparse Representation (ACA)

Problem: Dense matrix, vector multiplication is of order $\mathcal{O}(N_h^2)$ **Idea:**

Low rank approximation \rightarrow Adaptive Cross Approximation

M. Bebendorf [2001]

M. Bebendorf, S. Rjasanow [2001]

\rightarrow split the dense BE-matrix V_h into 'far-field' and 'near-field' contributions

$$V_h = V_h^{near} + V_h^{far}$$

BEM - Sparse Representation (ACA)

Let D_1, D_2 clusters corresponding to indices of V_h^{far} with

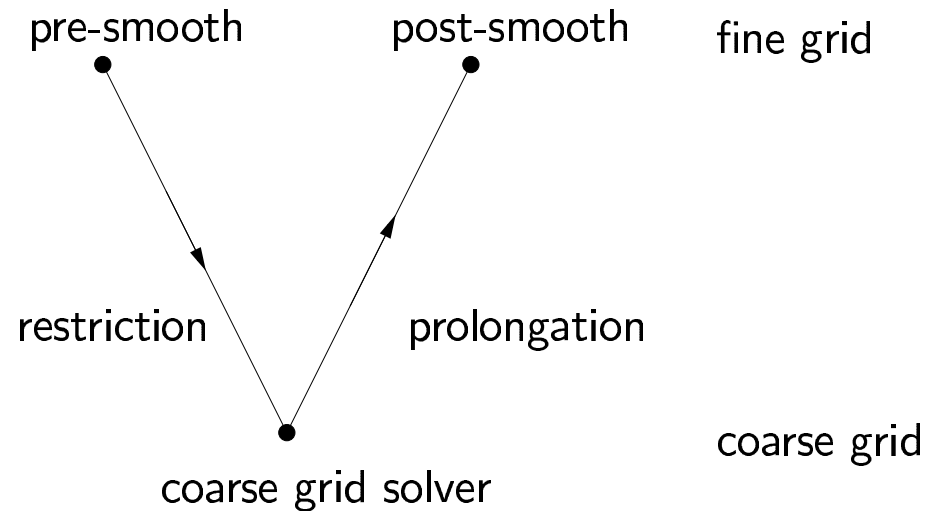
$$\text{diam } D_2 < \eta \text{ dist}(D_1, D_2)$$

→ η -admissible

find a low rank approximation $\tilde{A} = \sum_{i=1}^r u_i v_i^\top$
for some η -admissible matrix $A \in \mathbb{R}^{n \times m}$

$$\rightarrow \tilde{V}_h = V_h^{near} + \sum_{i=1}^{N_B} \sum_{j=1}^{r_i} u_j^i v_j^{i\top}$$

Multigrid Methods - Twogrid



Motivation: split the frequencies of the error

- smoother for highly oscillating contributions
- coarse grid correction for smooth components

Components of Multigrid Algorithms

1. Matrix Hierarchy

separate grids (GMG)

splitting into fine and coarse grid nodes (AMG)

2. Transfer operators

prolongation $P_h : X_H \mapsto X_h$, restriction $R_h = (P_h)^T : X_h \mapsto X_H$

3. Coarse grid operator

Galerkin's method: $K_H = P_h^T K_h P_h$

4. Smoothing operator

Gauss-Seidel method (FEM, Hyp.sing.Op.)

Bramble-Leyk-Pasciak smoother (Sing.Op.)

Multigrid - Smoothing

Single Layer Potential:

Problem: Converse behavior of eigenvalues and eigenfunctions w.r.t. Hypersingular operator

Idea: suggested by Bramble, Leyk and Pasciak:
The Analysis of Multigrid Algorithms for Pseudo-Differential Operators of Order Minus One [1994]

→ choose $H^{-1}(\Omega)$ inner product for MG development

→ only multiplications with a sparse matrix are needed

Multigrid - Smoothing

Consider an appropriate BLP-smoothing sweep

$$\underline{u}_h = \underline{u}_h + \tau_h A_h (\underline{f} - K_h \underline{u}_h)$$

with $0 < \tau_h < 1/\lambda_u$ and λ_u the largest eigenvalue of

$$K_h \underline{w} = \lambda A_h^{-1} \underline{w}.$$

Note, A_h is discretization of the boundary corresponding to the **Laplace-Beltrami** operator

Multigrid - Transfer Operators

Geometric Multigrid:

basis of coarse and fine level $X_H = \text{span } \Phi_i$, $X_h = \text{span } \phi_i$

$$\Phi_i = \sum_{j=1}^n p_{ij} \phi_j$$

→ Prolongation/Restriction Operators

$$v_H = P_h v_h, \quad V_H = P_h^\top V_h P_h$$

Algebraic Multigrid:

entries of P_h depend on the splitting into coarse node and fine nodes

$$\omega = \omega_C \cup \omega_F$$

Convergence Analysis

convergence for approximated single layer potential $\tilde{V}(\cdot, \cdot)$

→ uniform reduction per iteration

$$V(\mathcal{E}v, v) \leq (1 - 1/C)V(v, v)$$

→ less than full regularity & approximation

$$\|(I - P_{k-1})v\|^2 \leq c\lambda_k^{-1}V(v, v)$$

→ continuous form as well as matrix form

Convergence Analysis

proof for single layer potential \rightarrow

[1] J. Bramble, Z. Leyk and J. Pasciak.

The Analysis of Multigrid Algorithms for Pseudo-Differential Operators of Order Minus One. 1994

basically two assumptions \rightarrow

(A1) *lower estimate*

$$V(v, v) \leq \tilde{C}(V(P_1 v, v) + \sum_{k=2}^J \lambda_k^{-1} \|V_k P_k v\|_{-1}^2) \quad \forall v \in M$$

(A2) *upper estimate*

$$\|V_i v\|_{-1}^2 \leq \tilde{C}(\epsilon^{i-k})^2 \lambda_i V(v, v) \quad \forall v \in M_k \quad 1 \leq i \leq k \leq J \quad \epsilon < 1$$

Convergence Analysis

consider $\tilde{V}(\cdot, \cdot)$ as perturbed form of $V(\cdot, \cdot)$

→ conditions (A1), (A2) will also hold for $\tilde{V}(\cdot, \cdot)$

→ additional assumptions

(B1) spectral equivalence

$$c_1 V(v, v) \leq \tilde{V}(v, v) \leq c_2 V(v, v) \quad v \in M$$

(B2) approximation

$$|V(v, w) - \tilde{V}(v, w)| \leq c \lambda_J^{-\beta/2} |||v||| |||w||| \quad v, w \in M$$

$$\text{with } |||v|||^2 = V(v, v)$$

Convergence Analysis

(B1) induces

lower estimate (A1) for $\tilde{V}(\cdot, \cdot)$

(B1), (B2) and inequality $c(v, v) \leq V(v, v)$ induce

upper estimate (A2) for $\tilde{V}(\cdot, \cdot)$

→ uniform reduction per iteration for $\tilde{V}(\cdot, \cdot)$

Convergence Analysis

Verification for ACA Matrices

- low - rank approximation provides

$$\|V_h - \tilde{V}_h\|_F \leq \epsilon \|V_h\|_F.$$

- norm equivalence between spectral norm / Frobenius norm

$$\|V_h\|_2 \leq \|V_h\|_F \leq \sqrt{n} \|V_h\|_2 \quad V_h \in \mathbb{R}^{n \times n}$$

Convergence Analysis

one can show, that $\forall \underline{v} \in \mathbb{R}^n$

$$\begin{aligned}(1 - \epsilon\sqrt{N_h}\kappa(V_h)) \underline{v}^\top V_h \underline{v} &\leq \underline{v}^\top \tilde{V}_h \underline{v} \\ \underline{v}^\top \tilde{V}_h \underline{v} &\leq (1 + \epsilon\sqrt{N_h}\kappa(V_h)) \underline{v}^\top V_h \underline{v}\end{aligned}$$

→ verification of (B1)

Convergence Analysis

Further we have inequalities

$$\|u_h\|_{-1/2} \geq ch^{1/2} \|u_h\|_0,$$

$$\|\underline{u}_h\|_{\mathbb{R}^n} \leq ch^{-d/2} \|u_h\|_0$$

and

$$c_1 \|u_h\|_{-1/2}^2 \leq V(u_h, u_h) \leq c_2 \|u_h\|_{-1/2}^2.$$

$$\|V_h\|_2 \simeq h^d$$

Convergence Analysis

Remark, $\lambda_J \simeq h^{-1}$, thus we can estimate

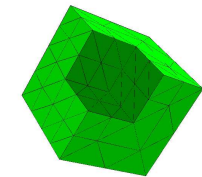
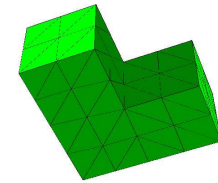
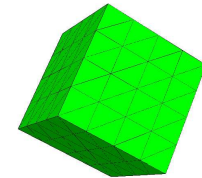
$$\begin{aligned} |V(v_h, w_h) - \tilde{V}(v_h, w_h)| &\leq \|V_h - \tilde{V}_h\|_2 \|\underline{v}_h\|_{\mathbb{R}^{N_h}} \|\underline{u}_h\|_{\mathbb{R}^{N_h}} \\ &\leq \epsilon \sqrt{N_h} \|V_h\|_2 h^{-d-1} \|v_h\|_{-1/2} \|u_h\|_{-1/2} \\ &\leq \epsilon \|V_h\|_2 h^{-1-3d/2} \|v_h\| \|u_h\| \\ &\leq c \epsilon h^{-1-d/2-\beta/2} \lambda_J^{-\beta/2} \|v_h\| \|u_h\| \end{aligned}$$

uniform reduction of perturbed bilinearform

$$\rightarrow \tilde{V}(\mathcal{E}v, v) \leq (1 - 1/C) \tilde{V}(v, v)$$

Numerical Results

- AMG program package PEBBLES
(www.numa.uni-linz.ac.at/Research/Projects/pebbles.html)
- BEM-Matrix entries by OSTBEM (O. Steinbach)
- Sparse representation of V_h (ACA)
- AMG/GMG preconditioner for CG - Full MG
- PC 2000MHz Athlon



Assembling Time AMG - GMG

L-Shape N_h	V_h [sec] Assembling	AMG [sec] Galerkin Projection	GMG [sec] Matrix Hierarchy
1792	6.0	2.0	0.9
7168	32.5	7.5	6.9
28672	158	30	40

Iteration Numbers - CPU Time

Number of Unknowns	AMG		GMG	
	PCG-Cycle [sec]	Iterations	PCG-Cycle [sec]	Iterations
L-Shape				
1792	0.1	6	0.1	7
7168	0.8	6	0.6	7
28672	4.2	9	2.9	7
114688	-	-	33*)	7
*) memory exceeded - r/w effects				
Cube				
3072	0.2	5	0.2	6
12288	1.7	8	1.1	7
49152	9.0	11	5.7	7
Fichera-Corner				
1920	0.1	14	0.1	15
7680	0.8	15	0.6	15
30720	5.0	17	3.2	15

Multigrid Preconditioner - Full Multigrid

Number of Unknowns	GMG		Full MG	
	PCG-Cycle [sec]	Iterations	Cycle [sec]	Iterations
L-Shape				
1792	0.1	7	0.1	10
7168	0.6	7	0.5	10
28672	2.9	7	2.8	9
Cube				
3072	0.2	6	0.2	8
12288	1.1	7	1.0	8
49152	5.7	7	5.2	8
Fichera-Corner				
1920	0.1	15	0.1	53
7680	0.6	15	0.6	52
30720	3.2	15	3.1	50

Grid Data - Level Data

Level	AMG	GMG
Cube		
fine 1	49152	49152
2	23828	12288
3	7311	3072
4	2025	768
coarse 5	625	-

Level	AMG	GMG
Fichera-Corner		
fine 1	30720	30720
2	14995	7680
3	4677	1920
coarse 4	1282	480

Conclusions and Outlook

- + GMG/AMG components for BE-matrices
 - + 2D/3D examples for dense/sparse BE-matrices
 - + First analysis results for GMG
-
- + Appropriate MG design for more complex geometries
 - + Analysis for AMG