

Modern Numerical Methods with Medical Applications

Part II: Multigrid Iteration

Wolfgang Hackbusch

Max-Planck-Institut für *Mathematik in den Naturwissenschaften*



Inselstr. 22-26, 04103 Leipzig, Germany
wh@mis.mpg.de

http://www.mis.mpg.de/scicomp/hackbusch_e.html

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1 Motivation

The FE stiffness matrix L_h is a sparse matrix of size $n_h \times n_h$, where n_h is very large. Typical value $n_h \gtrsim 1.000.000$.

For its solution one needs methods with a cost being (almost) **linear** in n_h .

Direct methods (Gauss elimination, Cholesky decomposition) cost up to $O(n_h^3)$ operations, traditional iterative methods cost $O(n_h h^{-1})$ to $O(n_h h^{-2})$ operations.

The **multigrid method** applies to rather general discretisations of elliptic PDEs and has linear cost.

Literature:

W.Hackbusch: Multi-Grid Methods and Applications. Springer 1985 and 2003
—: Iterative Solution of Large Sparse Systems of Equations, 2nd ed., Springer 2016

1.1 Linear Iterations

1.1.1 Notations

Linear system: $Lu = f$ with $L \in \mathbb{R}^{n \times n}$, $u, f \in \mathbb{R}^n$.

A general one-step method

$$u^j \mapsto u^{j+1} := \Phi(u^j, f)$$

is called a **linear iteration** if Φ is linear in both arguments:

$$\Phi(u, f) = Mu + Nf.$$

Consistency: The exact solution $u^* = L^{-1}f$ should be a fixed point of Φ for all f :

$$L^{-1}f = u^* = \Phi(u^*, f) = ML^{-1}f + Nf$$

This implies $L^{-1} = ML^{-1} + N$, i.e.,

$$M + NL = I \quad (\text{consistency condition}).$$

Then Φ becomes

$$\Phi(u, f) = u - N(Lu - f).$$

1.1.2 Convergence

The iteration error $u^j - u^*$ (u^* solution of $Lu = f$) satisfies

$$u^{j+1} - u^* = M (u^j - u^*) \quad \text{and therefore} \quad \|u^{j+1} - u^*\| \leq \|M\| \|u^j - u^*\|.$$

$\|M\| < 1$ is sufficient for convergence $u^j \rightarrow u^*$ ($\|M\|$: contraction number).

A necessary and sufficient condition for convergence is

$$\rho(M) < 1$$

where

$$\rho(M) := \max\{|\lambda| : \lambda \text{ eigenvalue of } M\}$$

is the *spectral radius*.

LEMMA: a) $\rho(M) \leq \|M\|$. b) $M = M^H \Rightarrow \rho(M) = \|M\|$.

1.1.3 Classical Examples of Iterations

Jacobi iteration: $N = D^{-1} (D = \text{diag}(M))$,
i.e. $u^j \mapsto u^{j+1} := u^j - D^{-1}(Lu^j - f)$.

```
procedure Jacobi( $u, f$ ); array  $u, u^{\text{old}}, f$ ; integer  $i, j$ ;  
begin  $u^{\text{old}} := u$ ; for all  $i$  do  $u[i] := u^{\text{old}}[i] - (\sum_j (L[i, j]u^{\text{old}}[j]) - f[i]) / L[i, i]$   
end;
```

Gauss-Seidel iteration:

```
procedure GS( $u, f$ ); array  $u, f$ ; integer  $i, j$ ;  
for  $i := 1$  to  $n$  do  $u[i] := u[i] - (\sum_j (L[i, j]u[j]) - f[i]) / L[i, i]$ ;
```

$\Rightarrow N = (L_{\text{lower}} + D)^{-1}L_{\text{upper}}$ where $L = L_{\text{lower}} + D + L_{\text{upper}}$ (lower triangular / upper triangular part)

Assume $L = L^H$. Then

Jacobi converges if $2D > L > 0$;

Gauss-Seidel converges if $L > 0$.

1.1.4 Speed of Convergence

Discretisation of second order pde with step size h .

\Rightarrow condition number $\|M\| \|M^{-1}\| = O(h^{-2})$

3D case: $n \sim h^{-3}$.

Jacobi and Gauss-Seidel: contraction number is $1 - O(h^2)$

SOR (successive overrelaxation): $1 - O(h)$

1.1.5 Cost of the iterative scheme

1 iteration step costs $O(n)$ operations (sparse matrix!)

Assume that we want $\|u^j - u^*\| \cong \varepsilon$ starting from $u^0 := 0$.

$(1 - O(h^\kappa))^m = \varepsilon$ requires $m = O(h^{-\kappa} |\log \varepsilon|)$ iterations

Cost of Jacobi or Gauss-Seidel: $O(nh^{-2} |\log \varepsilon|) = O(h^{-5} |\log \varepsilon|) = O(n^{5/3} |\log \varepsilon|)$

Cost of SOR: $O(nh^{-1} |\log \varepsilon|) = O(h^{-4} |\log \varepsilon|) = O(n^{4/3} |\log \varepsilon|)$

Optimal case would be a contraction number $\zeta < 1$ *independent* of h . Then the cost is $O(n |\log \varepsilon|)$. This is the case of the *multigrid method*.

We shall even obtain $O(n)$ for $\varepsilon = \text{discretisation error} = h^\kappa$.

The multigrid approach is based on two ingredients:

- smoothing property
- coarse-grid correction

1.2 Smoothing Property

1D Example: $-u'' = f$ in $[0,1]$ and $u(0) = u(1) = 0$

Discretisation: $h^{-2} [-u_h(x-h) + 2u_h(x) - u_h(x+h)] = f(x)$

This yields the system $L_h u_h = f_h$ with $u_h = [u_h(h), u_h(2h), u_h(3h), \dots, u_h(1-h)]^T$ and the sparse matrix

$$L_h = h^{-2} \begin{bmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & \ddots & \ddots & \ddots \\ & & & -1 & 2 \end{bmatrix} \in \mathbb{R}^{n_h \times n_h} \quad \text{with } n_h = \frac{1}{h} - 1.$$

The eigenvalue problem

$$L_h e_h = \lambda_h e_h$$

is solved by the eigenvectors

$$e_h^\mu(x) = \sin(\mu\pi x) \quad \text{for } x = h, 2h, 3h, \dots, 1-h$$

and eigenvalues

$$\lambda_h^\mu = 2(1 - \cos \pi h \mu) \quad \text{for } \mu = 1, \dots, n_h = \frac{1}{h} - 1$$

Jacobi iteration:

$$u_h^j \longmapsto u_h^{j+1} = u_h^j - D_h^{-1} (L_h u_h^j - f_h) = M_h u_h^j + D_h^{-1} f_h$$

with the iteration matrix $M_h := I - D_h^{-1} L_h$, where $D_h = \text{diag}(L_h)$.

Damped Jacobi iteration:

$$u_h^j \longmapsto u_h^{j+1} = u_h^j - \frac{1}{2} D_h^{-1} (L_h u_h^j - f_h) \Rightarrow$$

iteration matrix $M_h := I - \frac{1}{2} D_h^{-1} L_h$.

In this case, M_h is symmetric $\Rightarrow \|M_h\| = \rho(M_h) := \max\{|\text{eigenvalues of } M_h|\}$.

Eigenvalues of the iteration matrix: $\lambda_\mu = 1 - 4\omega \sin^2(\mu\pi h/2)$, $1 \leq \mu \leq n_h$,

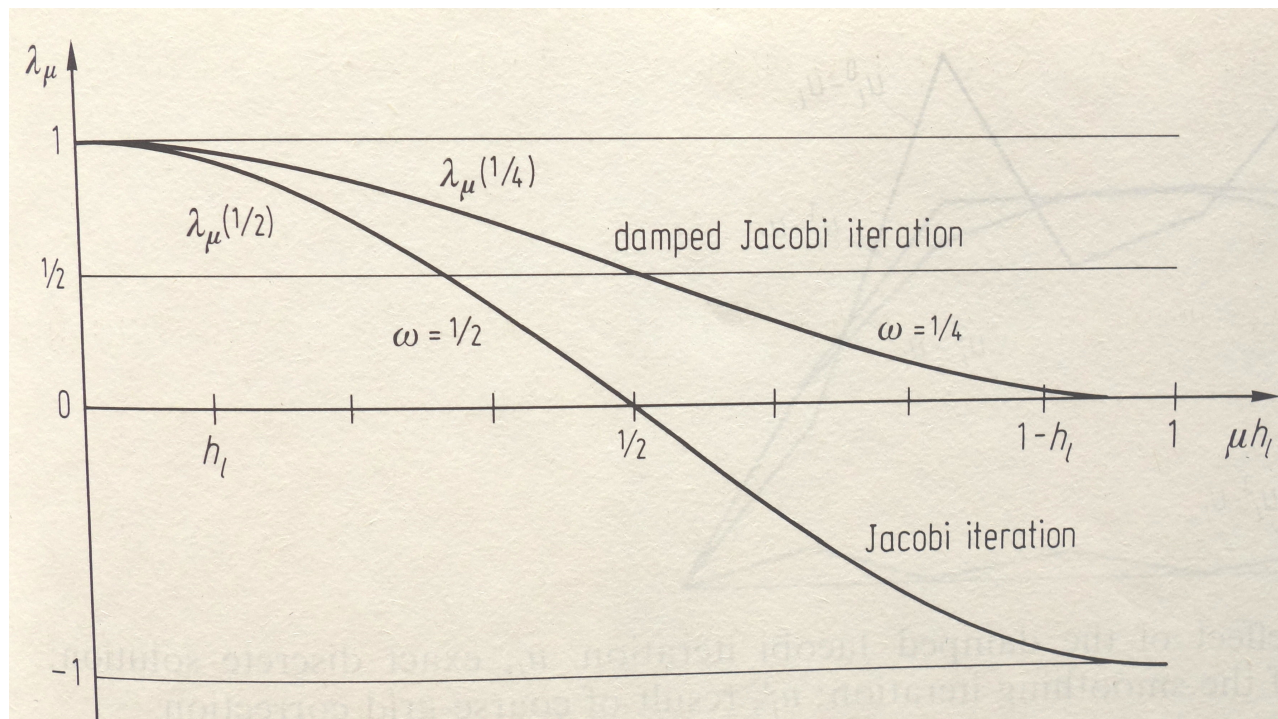
with $\omega = \begin{cases} 1/2 & \text{for standard Jacobi} \\ 1/4 & \text{for damped Jacobi} \end{cases}$

Splitting of $V_h := \mathbb{R}^{n_h} = V_{\text{low}} \oplus V_{\text{high}}$

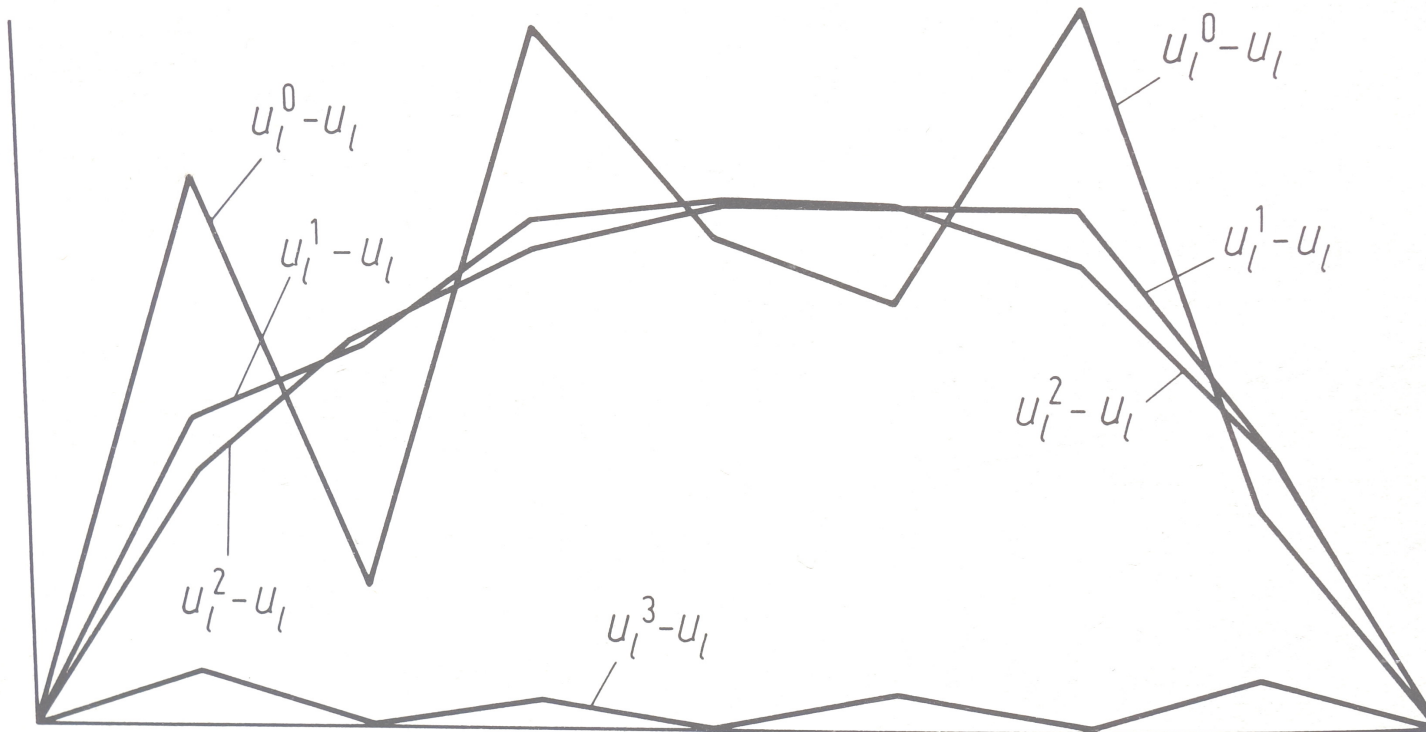
into $\begin{cases} \text{low-frequency part } V_{\text{low}} := \text{span}\{e_h^\mu : 1 \leq \mu \leq n_h/2\}, \\ \text{high-frequency part } V_{\text{high}} := \text{span}\{e_h^\mu : n_h/2 < \mu \leq n_h\} \end{cases}$

Conclusion for damped Jacobi:

Errors in V_{high} are reduced by a factor $\frac{1}{2}$ per iteration.



Smoothing Effect: After few steps of the damped Jacobi iteration the low-frequency part is dominating \Rightarrow The iteration error $u_h^j - u_h$ is smooth:



A smooth error with step size h can be well approximated by a grid function with step size $2h$!

Often used smoothing iteration: **Gauss-Seidel iteration**

1.3 Coarse-Grid Correction

Actual approximation for step size h : \bar{u}_h

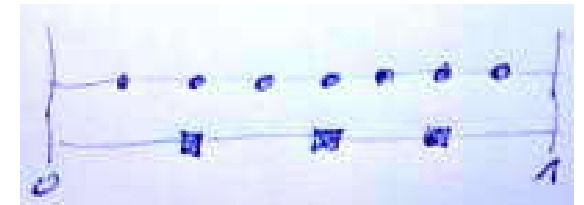
Its *defect* is

$$d_h := L_h \bar{u}_h - f_h.$$

The solution of $L_h v_h = d_h$ is the *exact correction*: $u_h = \bar{u}_h - v_h$.

Coarse-grid equation:

$$L_{2h} v_{2h} = d_{2h} \quad \text{with} \quad d_{2h}(x) := \frac{1}{4}d_h(x-h) + \frac{1}{2}d_h(x) + \frac{1}{4}d_h(x+h),$$



short: $d_{2h} = r d_h$ (restriction $r : V_h \rightarrow V_{2h}$)

Interpolation of v_{2h} : $p v_{2h}$ (prolongation $p : V_{2h} \rightarrow V_h$, Exercise: $p = 2r^T$)

Approximate correction: $u_h^{\text{new}} = \bar{u}_h - p v_{2h}$.

2 Two-Grid Iteration

u_ℓ^j given iterate (ℓ : level number corresponding to $h = h_\ell$, $h_{\ell-1} := 2h_\ell$)

smoothing step: ν steps of a smoothing iteration (e.g. damped Jacobi):

$$\bar{u}_\ell := \mathcal{S}_\ell^\nu(u_\ell^j, f_\ell)$$

coarse-grid correction:

$d_\ell := L_\ell \bar{u}_\ell - f_\ell$	defect
$d_{\ell-1} := r d_\ell$	restriction of the defect
$v_{\ell-1} := L_{\ell-1}^{-1} d_{\ell-1}$	exact solution of the coarse-grid equation
$u_\ell^{j+1} := \bar{u}_\ell - p v_{\ell-1}$	correction of \bar{u}_ℓ

The **two-grid iteration** is defined by $u_\ell^j \mapsto u_\ell^{j+1}$.

\Rightarrow error reduction independent of h_ℓ :

$$\|u_\ell^{j+1} - u_\ell\| \leq \rho \|u_\ell^j - u_\ell\| \quad \text{with } \rho < 1 \text{ for all } \ell$$

weak point: $L_{\ell-1}^{-1}$

Notation:

Here: grid sizes h and $2h$.

We can continue: $4h, 8h, \dots$

New notation: ℓ denotes the **level**.

For $\ell = 0$ we have a coarsest grid size h_0 and set

$$h_\ell = 2^\ell h_0.$$

For h_ℓ the index h in L_h, u_h, f_h is replaced by ℓ : $L_\ell u_\ell = f_\ell$.

Example: $\Omega = (0, 1)$, $h_0 = 1/2 \Rightarrow x = 1/2$ is the only grid point $\Rightarrow L_0$ is 1×1 ,
 $L_\ell \in \mathbb{R}^{n_\ell \times n_\ell}$ with $n_\ell = 2^{1+\ell} - 1$.

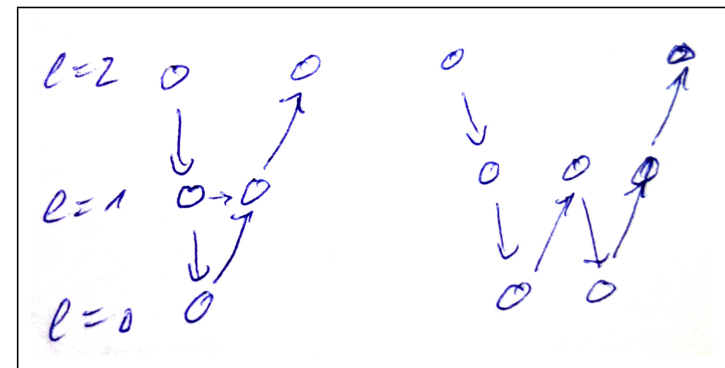
Algorithmic notation of the two-grid method:

```
procedure  $TGM(\ell, u, f)$ ; integer  $\ell$ ; array  $u, f$ ;  
if  $\ell = 0$  then  $u := L_0^{-1} * f$  else  
begin array  $v, d$ ;  
 $u := \mathcal{S}_\ell^v(u, f)$ ;  $d := r * (L_\ell * u - f)$ ;  $v := L_{\ell-1}^{-1} * d$ ;  $u := u - p * v$   
end;
```

3 Multi-Grid Iteration

```
procedure  $MGM(\ell, u, f)$ ; integer  $\ell$ ; array  $u, f$ ;  
if  $\ell = 0$  then  $u := L_0^{-1} * f$  else  
begin array  $v, d$ ;  
 $u := \mathcal{S}_\ell^v(u, f)$ ;  $d := r * (L_\ell * u - f)$ ;  
 $v := 0$ ; for  $j = 1(1)\gamma$  do  $MGM(\ell - 1, v, d)$ ;  
 $u := u - p * v$   
end;
```

V-cycle: $\gamma = 1$, W-cycle: $\gamma = 2$



Application to FE Equations

Simplest situation:

The finite-element subspaces satisfy

$$\mathcal{H}_{\ell-1} \subset \mathcal{H}_{\ell}$$

(nested FE spaces).

Then:

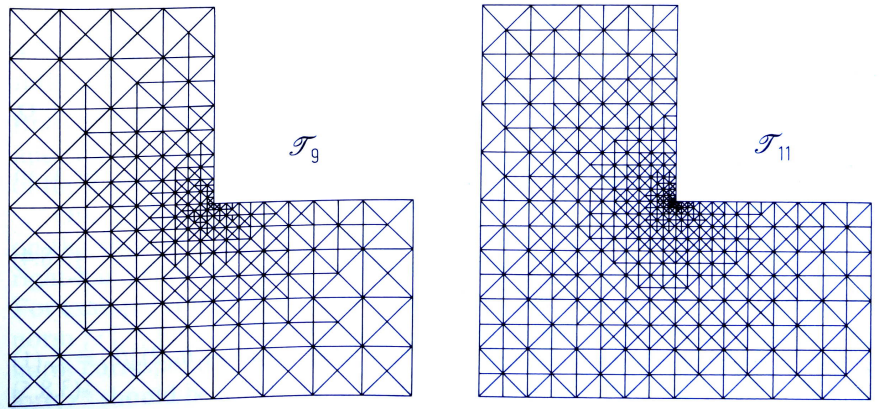
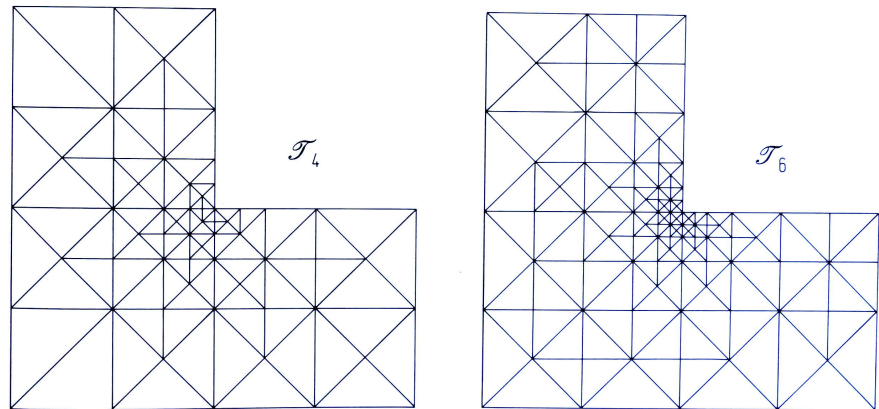
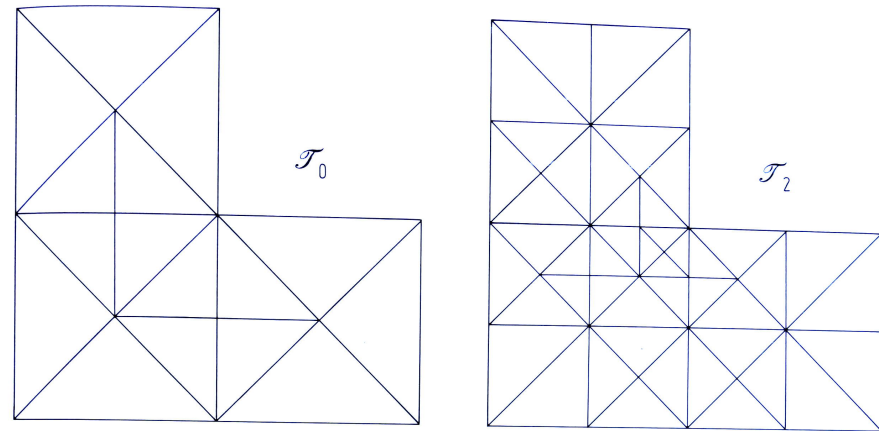
$$p : \mathcal{H}_{\ell-1} \rightarrow \mathcal{H}_{\ell} \text{ identity,}$$

r : transposed of p ,

$$L_{\ell-1} = r L_{\ell} p.$$

More difficult:

Given a finest FE space,
how to find coarser ones?

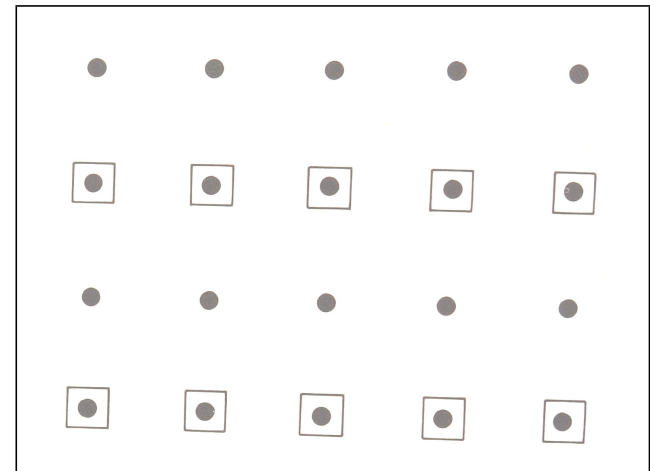


Applicability:

In principle, the multigrid iteration works for discretisations of elliptic PDEs.

The error reduction per iteration is independent of the grid size, but may depend on other parameters, e.g., on the **anisotropy**. Standard example:

$$-\varepsilon u_{xx} - u_{yy} = f \quad \text{for small } \varepsilon > 0.$$



Remedy: Coarsening only in y -direction:

In the general case, varying anisotropy directions etc., the **construction of the coarser grid** is nontrivial.

3.1 Algebraic Multigrid Iteration

J.W. Ruge, K. Stüben: Algebraic multigrid (AMG). In: Multigrid Methods, Vol. 5 of Frontiers in Applied Mathematics (ed. S. McCormick), SIAM Philadelphia, pp. 73-130, 1986

Coarsening: Let ω_ℓ be the FE grid points (nodal points) at level ℓ corresponding to the FE space H_ℓ . Define a suitable splitting

$$\omega_\ell = \omega_F \dot{\cup} \omega_C$$

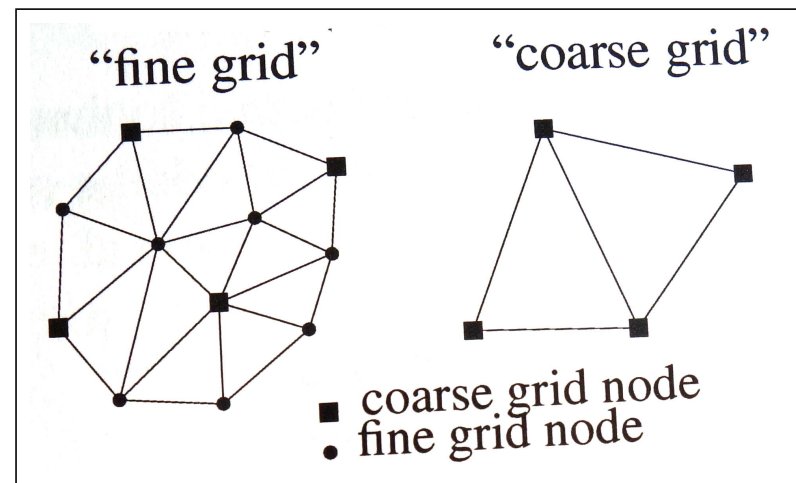
into sets of fine-grid nodes (ω_F) and coarse-grid nodes (ω_C).
 $\omega_{\ell-1} := \omega_C$ defines the nodal values of the FE space $H_{\ell-1}$.

Prolongation: $p : H_{\ell-1} \rightarrow H_\ell$ interpolation at the nodes ω_ℓ .

Restriction: r transposed of p .

Coarse-grid matrix: $L_{\ell-1} = rL_\ell p$.

Smoothing iteration: Gauss-Seidel iteration



Literature for AMG:

G. Haase, U. Langer, S. Reitzinger, J. Schöberl: A General Approach to Algebraic Multigrid Methods, March 2001 in

[https://www.researchgate.net/publication/](https://www.researchgate.net/publication/2370058_A_General_Approach_to_Algebraic_Multigrid_Methods)

[2370058_A_General_Approach_to_Algebraic_Multigrid_Methods](https://www.researchgate.net/publication/2370058_A_General_Approach_to_Algebraic_Multigrid_Methods)

and

C.H. Wolters, M. Kuhn, A. Anwander, S. Reitzinger: A parallel algebraic multigrid solver for finite element method based source localization in the human brain. *Computing and Visualization in Science* 5(3), pp.165–177 (2002).

4 Nested Iteration

PDE $Lu = f$. Discretizations at all levels $0 \leq k \leq \ell$ by $L_k u_k = f_k$.

Trivial statements:

- 1) The iterate u_ℓ^{j+1} of an iteration $u_\ell^j \mapsto u_\ell^{j+1}$ is the better, the better the starting iterate u_ℓ^j is.
- 2) Solving $L_{\ell-1} u_{\ell-1} = f_{\ell-1}$ (approximately) is cheaper than solving $L_\ell u_\ell = f_\ell$ (lower dimension!).
- 3) $pu_{\ell-1}$ approximates u_ℓ

Idea: Use $pu_{\ell-1}$ as starting iterate for $u_\ell^j \mapsto u_\ell^{j+1}$.

Nested iteration:

$$\tilde{u}_0 := L_0^{-1} f_0;$$

for $k := 1$ (1) ℓ **do**

begin $\tilde{u}_k := p\tilde{u}_{k-1}$; **for** $j := 1$ (1) i **do** $MGM(k, \tilde{u}_k, f_k)$ **end**;

Analysis of the nested iteration:

Assumptions: 1) multigrid convergence:

$$\begin{aligned} \|u_k^{j+1} - u_k\| &\leq \zeta_k \|u_k^j - u_k\|, & u_k &:= L_k^{-1} f_k, \\ \zeta &:= \max \{\zeta_k : 1 \leq k \leq \ell\} < 1. \end{aligned}$$

2) interlevel convergence:

$$\|pu_{k-1} - u_k\| \leq C_1 h_k^\kappa \quad (1 \leq k \leq \ell),$$

$$3) \quad C_2 := C_{20} \cdot C_{21} \quad \text{with} \quad \|p\| \leq C_{20}, \quad h_{k-1}/h_k \leq C_{21}.$$

Theorem: Under the assumption from above and $C_2 \zeta^i < 1$, the nested iteration yields \tilde{u}_k with

$$\|\tilde{u}_k - u_k\| \leq \frac{\zeta^i}{1 - C_2 \zeta^i} C_1 h_k^\kappa \quad (1 \leq k \leq \ell).$$

Proof: Exercise

Cost of the Multi-Grid Iteration:

Assume

$$\frac{n_{\ell-1}}{n_\ell} \leq C_H, \quad \vartheta := \gamma C_H < 1$$

(standard value: $C_H = 2^{-d}$ for problems in \mathbb{R}^d).

Then: $MGM(\ell, \cdot, \cdot)$ requires $C_\ell n_\ell$ operations, where

$$C_\ell < \frac{\nu C_S + C_D + C_C}{1 - \vartheta} + \vartheta^{\ell-1} \frac{C_0}{n_1}.$$

Proof: **Exercise**

Cost of the nested iteration:

Using $C_\ell \lesssim \frac{\nu C_S + C_D + C_C}{1 - \vartheta}$, the cost of the nested iteration with parameter i is bounded by

$$\sum_{k=1}^{\ell} i C_k n_k \leq i \sum_{k=1}^{\ell} C_H^{\ell-k} C_\ell n_\ell < \frac{i}{1 - C_H} C_\ell n_\ell.$$

operation	cost
$S_\ell(u_\ell, f_\ell)$	$\leq C_S n_\ell$
$r(L_\ell u_\ell - f_\ell)$	$\leq C_D n_\ell$
$u_\ell - pu_{\ell-1}$	$\leq C_C n_\ell$
$L_0^{-1} f_0$	$\leq C_0$

5 Convergence Analysis of the Two-Grid Iteration

Any linear iteration solving $L_\ell u_\ell := f_\ell$ is of the form

$$u_\ell^{j+1} = \Phi(u_\ell^j, f_\ell) = M_\ell u_\ell^j + N_\ell f_\ell \quad \text{with } M_\ell + N_\ell L_\ell = I.$$

M_ℓ is called the **iteration matrix**.

Let S_ℓ be the iteration matrix of the smoothing iteration.

Exercise: The iteration matrix of the two-grid iteration with ν smoothing iteration steps is

$$M_\ell(\nu) := \left[I - pL_{\ell-1}^{-1}rL_\ell \right] S_\ell^\nu.$$

Hint: Let M'_ℓ and M''_ℓ be the respective iteration matrices of two linear iterations

$$u_\ell^j \mapsto u_\ell^{j+1} = \Phi'(u_\ell^j, f_\ell) \quad \text{and} \quad v_\ell^j \mapsto v_\ell^{j+1} = \Phi''(v_\ell^j, f_\ell).$$

Then the product of both iterations is $\Phi = \Phi'' \circ \Phi'$ with

$$w_\ell^j \mapsto w_\ell^{j+1} := \Phi''(\Phi'(w_\ell^j, f_\ell), f_\ell) \quad \text{and iteration matrix} \quad M_\ell := M'_\ell M''_\ell.$$

Simplified Convergence Analysis

$$M_\ell(\nu) = [I - pL_{\ell-1}^{-1}rL_\ell] S_\ell^\nu = [L_\ell^{-1} - pL_{\ell-1}^{-1}r] [L_\ell S_\ell^\nu].$$

Smoothing property:

$$\|L_\ell S_\ell^\nu\| \leq \eta(\nu) h_\ell^{-2} \quad \text{for all } \nu \geq 1 \text{ and } \ell \geq 1 \text{ with } \eta(\nu) \rightarrow 0 \text{ as } \nu \rightarrow \infty.$$

Approximation property: $\|L_\ell^{-1} - pL_{\ell-1}^{-1}r\| \leq C_A h_\ell^2.$

Combination of both inequalities yields

$$\|M_\ell(\nu)\| \leq C_A \eta(\nu)$$

and for sufficiently large ν we have

$$\|M_\ell(\nu)\| \leq \zeta < 1 \quad \text{implying} \quad \|u_\ell^{j+1} - u_\ell\| \leq \zeta \|u_\ell^j - u_\ell\|.$$

5.0.1 Smoothing Property

Example: L_ℓ symmetric with diagonal $D_\ell = 4h_\ell^{-2}I$ (5-point discretisation) and $\|L_\ell\| \leq 8h_\ell^{-2}$

Damped Jacobi iteration $u_\ell^j \mapsto u_\ell^{j+1} = u_\ell^j - \frac{1}{2}D_\ell^{-1} (L_\ell u_\ell^j - f_\ell)$.

Iteration matrix: $S_\ell = I - \omega L_\ell$ with $\omega = \frac{1}{2} (4h_\ell^{-2})^{-1} = \frac{1}{8}h_\ell^2$.

Euclidean norm: $\|L_\ell S_\ell^\nu\| = \|L_\ell (I - \omega L_\ell)^\nu\|$,

eigenvalues of L_ℓ between 0 and $8h_\ell^{-2} = 1/\omega$, \Rightarrow

$$\begin{aligned} \|L_\ell S_\ell^\nu\| &\leq \max \left\{ \lambda (1 - \omega\lambda)^\nu : 0 \leq \lambda \leq \frac{1}{\omega} \right\} \stackrel{\mu := \omega\lambda}{=} \frac{1}{\omega} \max \{ \mu (1 - \mu)^\nu : 0 \leq \mu \leq 1 \} \\ &= 8h_\ell^{-2} \eta_0(\nu). \end{aligned}$$

Exercise: $\eta_0(\nu) := \max \{ \mu (1 - \mu)^\nu : 0 \leq \mu \leq 1 \}$ satisfies

$$\eta_0(\nu) = \frac{1}{e\nu} + O(\nu^{-2}), \quad \eta_0(\nu) \leq \frac{3/8}{\nu + 1/2} \text{ for } \nu \geq 1.$$

5.0.2 Approximation Property

PDE: $Lu = f$, nested FEM $\rightarrow L_\ell u_\ell = f_\ell$ and $L_{\ell-1} u_{\ell-1} = f_{\ell-1}$ with $f_\ell := R_\ell f$ and

$u_\ell \in U_\ell$ finite-element coefficients, $P_\ell u_\ell \in L^2(\Omega)$ corresponding finite-element function, $P_\ell : U_\ell \rightarrow L^2(\Omega)$,

Similarly: $u_{\ell-1}$ and $P_{\ell-1} u_{\ell-1} \in L^2(\Omega)$. Then

$$P_{\ell-1} = P_\ell p : U_{\ell-1} \rightarrow L^2(\Omega).$$

The adjoint mappings are $R_\ell = P_\ell^*$, $r = p^*$. In particular, $f_\ell := R_\ell f$ and $f_{\ell-1} := R_{\ell-1} f$, $R_{\ell-1} = r R_\ell$

Under suitable conditions (smooth coefficients, Ω convex): If $f \in L^2(\Omega)$, then $u \in H^2(\Omega)$ and

$$\left\| \left(L^{-1} - P_\ell L_\ell^{-1} R_\ell \right) f \right\|_{L^2} = \left\| L^{-1} f - P_\ell L_\ell^{-1} f_\ell \right\|_{L^2} = \|u - P_\ell u_\ell\|_{L^2} \leq Ch_\ell^2 \|f\|_{L^2}.$$

Repeated: $\left\| \left(L^{-1} - P_\ell L_\ell^{-1} R_\ell \right) f \right\|_{L^2} \leq C h_\ell^2 \|f\|_{L^2}.$

Similarly, $\left\| \left(L^{-1} - P_{\ell-1} L_{\ell-1}^{-1} R_{\ell-1} \right) f \right\|_{L^2} \leq C h_{\ell-1}^2 \|f\|_{L^2}.$

Triangle inequality:

$$\left\| \left(P_\ell L_\ell^{-1} R_\ell - P_{\ell-1} L_{\ell-1}^{-1} R_{\ell-1} \right) f \right\|_{L^2} \leq C \left(h_{\ell-1}^2 + h_\ell^2 \right) \|f\|_{L^2}.$$

$$h_{\ell-1} \leq c h_\ell \quad \Rightarrow \quad \left\| P_\ell L_\ell^{-1} R_\ell - P_{\ell-1} L_{\ell-1}^{-1} R_{\ell-1} \right\|_{L^2 \leftarrow L^2} \leq C \left(c^2 + 1 \right) h_\ell^2 \quad \Rightarrow$$

$$P_\ell L_\ell^{-1} R_\ell - P_{\ell-1} L_{\ell-1}^{-1} R_{\ell-1} = P_\ell L_\ell^{-1} R_\ell - P_\ell p L_{\ell-1}^{-1} r R_\ell = P_\ell \left(L_\ell^{-1} - p L_{\ell-1}^{-1} r \right) R_\ell.$$

$$\|P_\ell u_\ell\|_{L^2} \geq C_P \|u_\ell\| \quad \Rightarrow$$

$$\begin{aligned} \left\| L_\ell^{-1} - p L_{\ell-1}^{-1} r \right\| &\leq C_P^{-2} \left\| P_\ell \left(L_\ell^{-1} - p L_{\ell-1}^{-1} r \right) R_\ell \right\|_{L^2 \leftarrow L^2} \\ &\leq C_P^{-2} C \left(c^2 + 1 \right) h_\ell^2 = C_A h_\ell^2 \quad \text{with } C_A := C_P^{-2} C \left(c^2 + 1 \right). \end{aligned}$$

\Rightarrow Approximation Property

6 Adjoint and Symmetric Iterations

Any linear iteration solving $Lu := f$ is of the form $u^{j+1} = \Phi(u^j, f, L)$ with

$$\Phi(u, f, L) := Mu + Nf = u - N(Lu - f) \quad \text{since } M + NL = I.$$

Here, N depends on L . Notation: $N = N[L]$.

DEFINITION: (a) Given a linear iteration $\Phi(\cdot, \cdot, L)$, the corresponding **adjoint iteration** is defined by

$$\Phi^*(u, f, L) := u - (N[L^H])^H (Lu - f).$$

(b) A linear iteration Φ is **symmetric**, if $\Phi = \Phi^*$ (i.e., $N[L] = N[L^H]^H$).

EXERCISE: (a) The adjoint iteration of the Gauss-Seidel iteration is the backward Gauss-Seidel iteration.

(b) The product $\Phi^* \circ \Phi$ is a symmetric iteration.

(c) If Ψ is a symmetric iteration, then $\Phi^* \circ \Psi \circ \Phi$ is symmetric.

(d) Φ symmetric and L symmetric matrix \implies also N is symmetric.

(e) Φ symmetric and L positive definite $\implies L^{1/2}ML^{-1/2}$ is symmetric [essential for application of conjugate gradient methods!]

(f) Assume $p = r^H$ and $L_{\ell-1} = rL_{\ell}p$. Prove: The coarse-grid iteration is a symmetric iteration.

6.1 Symmetric Multigrid Iteration

The smoothing iteration \mathcal{S}_ℓ is now denoted as pre-smoothing $\mathcal{S}_{\ell,\text{pre}}$, while

$$\mathcal{S}_{\ell,\text{post}} := \mathcal{S}_{\ell,\text{pre}}^*$$

is used as post-smoothing (e.g., forward and backward Gauss-Seidel iteration).

```
procedure  $MGM(\ell, u, f)$ ; integer  $\ell$ ; array  $u, f$ ;  
if  $\ell = 0$  then  $u := L_0^{-1} * f$  else  
begin array  $v, d$ ;  
 $u := \mathcal{S}_{\ell,\text{pre}}^\nu(u, f)$ ;  $d := r * (L_\ell * u - f)$ ;  
 $v := 0$ ; for  $j = 1(1)\gamma$  do  $MGM(\ell - 1, v, d)$ ;  
 $u := u - p * v$ ;  
 $u := \mathcal{S}_{\ell,\text{post}}^\nu(u, f)$   
end;
```

Prove: This MGM is a symmetric iteration (suited for cg methods).

Without symmetry: combination with generalised cg methods possible.