

Convergence Analysis of a Two-Grid Method for Nonsymmetric Positive Definite Problems

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Outline

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- 2 Exact two-grid method
- 3 Convergence analysis
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Introduction

$$Ax = b$$

where $A \in \mathbb{R}^{n \times n}$ is nonsymmetric but positive definite, namely

$$v^T A v > 0 \quad \forall v \in \mathbb{R}^n \setminus \{0\}$$

e.g. discretization of convection-diffusion equations.



A-splittings

$$A = A_{sym} + A_{skew}$$

where

$$A_{sym} = \frac{1}{2}(A + A^T) \quad A_{skew} = \frac{1}{2}(A - A^T)$$

n.b.

A_{sym} is positive definite iff A is positive definite.

A-splittings

$$A = M - N$$

$$x_{k+1} = M^{-1}N x_k + M^{-1}b$$

$$= (I - M^{-1}A) x_k + M^{-1}b$$

$$= x_k + M^{-1}(b - Ax_k)$$

recall

convergence iif $\rho(I - M^{-1}A) < 1$

Assumptions

- Let $M \in \mathbb{R}^{n \times n}$ be an SPD smoother such that $\|I - M^{-1}A\|_M \leq 1$
- Let $R \in \mathbb{R}^{n_c \times n}$ be a restriction matrix of rank n_c
- Let $P \in \mathbb{R}^{n \times n_c}$ be a prolongation matrix of rank n_c
- The coarse-grid matrix $A_c := RAP \in \mathbb{R}^{n_c \times n_c}$ is nonsingular

aim: find the "ideal" R and P

Remark

$$\begin{aligned}\|I - M^{-1}A\|_M^2 &= \|M^{-\frac{1}{2}}(I - M^{-1}A)M^{\frac{1}{2}}\|_2^2 \\ &= \lambda_{\max}((I - M^{-\frac{1}{2}}AM^{\frac{1}{2}})(I - M^{-\frac{1}{2}}A^T M^{\frac{1}{2}})) \leq 1\end{aligned}$$

that is

$$\lambda_{\min}(M^{-\frac{1}{2}}\tilde{A}M^{\frac{1}{2}}) \geq 0$$

where

$$\tilde{A} = A + A^T - AM^{-1}A^T$$

n.b. $\|I - M^{-1}A\|_M \leq 1$ iff \tilde{A} is positive semidefinite.

Algorithm: exact two-grid method

- 1 smoothing : $x^{(1)} \leftarrow x^{(0)} + M^{-1}(b - Ax^{(0)})$
- 2 restriction : $r_c \leftarrow R(b - Ax^{(1)})$
- 3 coarse-grid correction : $e_c \leftarrow A_c^{-1} r_c$
- 4 prolongation : $x_{TG} \leftarrow x^{(1)} + P e_c$

Error reduction processes

$$x - x^{(1)} = (I - M^{-1}A)(x - x^{(0)})$$

$$x - x_{TG} = (I - \Pi_A)(x - x^{(1)})$$

where

$$\Pi_A := PA_c^{-1}RA$$

then

$$\|x - x^{(1)}\|_M \leq \|I - M^{-1}A\|_M \|x - x^{(0)}\|_M$$

$$\|x - x_{TG}\|_M \leq \|I - \Pi_A\|_M \|x - x^{(1)}\|_M$$

Projection $\Pi_A := P A_C^{-1} R A$

- Π_A is a projection along $\text{null}(RA)$ onto the $\text{range}(P)$
- For any sub-multiplicative norm: $\|I - \Pi_A\| \geq 1$
- $\|I - \Pi_A\|_M = 1 \iff \Pi_A = M^{-1} \Pi_A^T M$
- remark: in SPD problems, the usual choice $P = R^T$ yields

$$\|I - \Pi_A\|_A = \|I - R^T (R A R^T)^{-1} R A\|_A = 1$$

Prolongation P_*

It suffices to choose prolongation P such that $\Pi_A = M^{-1}A^T R^T (RAP)^{-T} P^T M$
n.b.

$$\text{range}(P) = \text{range}(M^{-1}A^T R^T)$$

$$\text{null}(RA) = \text{null}(P^T M)$$

Satisfied by $P = M^{-1}A^T R^T W$, with W nonsingular.

Taking $W = I$ yields

$$P_* = M^{-1}A^T R^T$$

Error propagation matrix E_{TG}

$$x - x_{TG} = E_{TG}(x - x^{(0)})$$

where

$$E_{TG} = (I - \Pi_A)(I - M^{-1}A)$$

Then

$$\|x - x_{TG}\|_M \leq \|E_{TG}\|_M \|x - x^{(0)}\|_M$$

with

$$\|E_{TG}\|_M = \|(I - M^{\frac{1}{2}} \Pi_A M^{-\frac{1}{2}})(I - M^{-\frac{1}{2}} A M^{-\frac{1}{2}})\|_2$$

A technical lemma ...

Lemma 3.1

Let \tilde{A} and Π_A be defined as above. Then

$$\text{null}(\tilde{A}) \cap \text{null}(RA) = \{0\} \quad (3.1)$$

if and only if $\text{rank}(\tilde{A}^{\frac{1}{2}}(I - \Pi_A)) = n - n_c$.

remark:

... which provides a sufficient and necessary condition for

$$\|E_{TG}\|_M < 1$$

M -convergence factor

Theorem 3.3

Under the assumptions of the exact two-grid algorithm, the condition (3.1), and using prolongation P_* , the M -convergence factor can be characterized as

$$\|E_{TG}\|_M = \sqrt{1 - \sigma_{TG}}$$

with

$$\sigma_{TG} = \lambda_{\min}^+(M^{-1}\tilde{A}(I - \Pi_A))$$

where \tilde{A} and Π_A are defined as above.

Proof of theorem 3.3

If $P = P_*$, then

$$A_C = RAP_* = P_*^T MP_*$$

and

$$\Pi_A = P_* A_C^{-1} RA = P_*(P_*^T MP_*)^{-1} P_*^T M$$

Let

$$\Pi = M^{\frac{1}{2}} \Pi_A M^{-\frac{1}{2}}$$

Then

$$\Pi = M^{\frac{1}{2}} P_*(P_*^T MP_*)^{-1} P_*^T M^{\frac{1}{2}}$$

Proof of theorem 3.3

Since $\Pi^\top = \Pi = \Pi^2$ and $\text{rank}(\Pi) = n_c$, there exists an $n \times n$ orthogonal matrix Q such that

$$Q^\top \Pi Q = \begin{bmatrix} I_{n_c} & 0 \\ 0 & 0 \end{bmatrix}$$

Recall

$$\begin{aligned} \|E_{TG}\|_M^2 &= \|(I - \Pi)(I - M^{-\frac{1}{2}} A M^{-\frac{1}{2}})\|_2^2 \\ &= \lambda_{\max}((I - M^{-\frac{1}{2}} A^\top M^{-\frac{1}{2}})(I - \Pi)(I - M^{-\frac{1}{2}} A M^{-\frac{1}{2}})) \\ &= \lambda_{\max}((I - M^{-\frac{1}{2}} A M^{-\frac{1}{2}})(I - M^{-\frac{1}{2}} A^\top M^{-\frac{1}{2}})(I - \Pi)) \\ &= \lambda_{\max}((I - M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}})(I - \Pi)) \\ &= 1 - \lambda_{\min}(\Pi - M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}}(I - \Pi)) \end{aligned}$$

Proof of theorem 3.3

Let

$$Q^T M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} Q = \begin{bmatrix} X_1 & X_2 \\ X_2^T & X_3 \end{bmatrix}$$

where $X_1 \in \mathbb{R}^{n_c \times n_c}$, $X_2 \in \mathbb{R}^{n_c \times (n-n_c)}$, and $X_3 \in \mathbb{R}^{(n-n_c) \times (n-n_c)}$.

The positive semidefiniteness of $Q^T M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} Q$ implies that of X_3 . From the relation

$$\begin{aligned} I - Q^T M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} Q &= Q^T (I - M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}}) Q \\ &= Q^T (M^{-\frac{1}{2}} A M^{-\frac{1}{2}}) (M^{-\frac{1}{2}} A^T M^{-\frac{1}{2}}) Q \end{aligned}$$

we deduce that $I_{(n-n_c) \times (n-n_c)} - X_3$ is SPSD. It follows that $\lambda(X_3) \in [0, 1]$.

Proof of theorem 3.3

Direct computation yields

$$\Pi + M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} (I - \Pi) = Q \begin{bmatrix} I_{n_c} & X_2 \\ 0 & X_3 \end{bmatrix} Q^T$$

Then

$$\begin{aligned} \|E_{TG}\|_M^2 &= 1 - \lambda_{\min}(\Pi + M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} (I - \Pi)) \\ &= 1 - \min\{1, \lambda_{\min}(X_3)\} \\ &= 1 - \lambda_{\min}(X_3) \end{aligned}$$

Proof of theorem 3.3

Since

$$(I - \Pi)M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}}(I - \Pi) = Q \begin{bmatrix} 0 & 0 \\ 0 & X_3 \end{bmatrix} Q^\top$$

we obtain

$$\begin{aligned} \text{rank}(X_3) &= \text{rank}((I - \Pi)M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}}(I - \Pi)) \\ &= \text{rank}(\tilde{A}^{\frac{1}{2}} M^{-\frac{1}{2}}(I - \Pi)) \\ &= \text{rank}(\tilde{A}^{\frac{1}{2}}(I - \Pi)) = n - n_c \end{aligned}$$

where we have used Lemma 3.1. This means X_3 is SPD, i.e. $\lambda_{\min}(X_3) > 0$.



Proof of theorem 3.3

Due to

$$M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} (I - \Pi) = Q \begin{bmatrix} 0 & X_2 \\ 0 & X_3 \end{bmatrix} Q^T$$

it follows that

$$\lambda_{\min}(X_3) = \lambda_{\min}^+(M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} (I - \Pi))$$

Thus,

$$\begin{aligned} \|E_{TG}\|_M^2 &= 1 - \lambda_{\min}^+(M^{-\frac{1}{2}} \tilde{A} M^{-\frac{1}{2}} (I - \Pi)) \\ &= 1 - \lambda_{\min}^+(M^{-1} \tilde{A} M^{-\frac{1}{2}} (I - \Pi) M^{\frac{1}{2}}) \\ &= 1 - \lambda_{\min}^+(M^{-1} \tilde{A} (I - \Pi_A)) \end{aligned}$$



Optimal restriction

Theorem 3.5

Let \tilde{A} be defined as above, and let $\{(\mu_i, v_i)\}_{i=1}^n$ be the eigenpairs of the generalized eigenvalue problem

$$\tilde{A} = \mu M v$$

where

$$\mu_1 \leq \mu_2 \leq \dots \leq \mu_n, \quad v_i^T M v_j = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{if } i \neq j. \end{cases}$$

Under the assumptions of Theorem 3.3, it holds that

$$\|E_{TG}\|_M^2 \geq \sqrt{1 - \mu_{n_c+1}}$$

with equality if $\text{null}(RA) = \text{span}\{v_{n_c+1}, \dots, v_n\}$.

Summary

- Choice of the smoother induced M -norm to measure the two-grid convergence

$$\|x - x_{TG}\|_M \leq \|E_{TG}\|_M \|x - x^{(0)}\|_M, \quad E_{TG} = (I - \Pi_A)(I - M^{-1}A)$$

- Prolongation operator $P_* = M^{-1}A^T R^T$ such that $\|I - \Pi_A\|_M = 1$
- Lemma 3.1 provides a sufficient and necessary condition for $\|E_{TG}\|_M < 1$
- Theorem 3.3 establishes an identity for characterizing the convergence factor

$$\|E_{TG}\|_M = \sqrt{1 - \sigma_{TG}}, \quad \sigma_{TG} = \lambda_{\min}^+(M^{-1}\tilde{A}(I - \Pi_A))$$

- Analysis on the influence of $\text{range}(R^T)$ on $\|E_{TG}\|_M$, based on the generalized eigenvalue problem

$$\tilde{A} = \mu M v$$

Questions?

thank you for your attention!