



Optimized Schwarz algorithms on non overlapping grids for anisotropic elliptic operators in the framework of DDFV schemes

Florence Hubert - Aix-Marseille University

work in collaboration with Martin Gander, Laurence Halpern, Stella Krell

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Some numerical challenges

Strong anisotropy on complex domain



The domain that can naturally be split into subdomains \rightsquigarrow How behave the Schwarz methods in such a case?

On Schwarz algorithms

Existence and uniqueness of harmonic functions on general domain

$$-\Delta u = 0 \text{ on } \Omega = \Omega_1 \cup \Omega_2, u = g \text{ on } \partial \Omega$$





1843 - 1921

Through an interative process \rightsquigarrow On the disk

 \rightsquigarrow On the rectangle

- $\begin{cases} -\Delta u_1^l = 0 \text{ on } \Omega_1 \\ u_1^l = g \text{ on } \partial\Omega \cap \partial\Omega_1 \\ u_1^l = u_2^{l-1} \text{ on } \Gamma_1 \end{cases} \qquad \qquad \begin{cases} -\Delta u_2^l = 0 \text{ on } \Omega_2 \\ u_2^l = g \text{ on } \partial\Omega \cap \partial\Omega_2 \\ u_2^l = u_1^l \text{ on } \Gamma_2 \end{cases}$
- called the classical **alternative** Schwarz method.
- Convergence proved by H. A. Schwarz in 1869 thanks to maximum principle argument.

On Schwarz algorithms

Existence and uniqueness of harmonic functions on general domain

$$-\Delta u = 0 \text{ on } \Omega = \Omega_1 \cup \Omega_2, u = g \text{ on } \partial \Omega$$





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- called the classical **parallel** Schwarz method.
- convergence proved by P.L. Lions in 1988 thanks to Fourier expansion.

Schwarz algorithm for nonoverlapping subdomains

 \rightsquigarrow we will focus on nonoverlapping subdomains in this talk !

$$Lu = f$$
 on $\Omega = \bigcup \Omega_i$, $u = g$ on $\partial \Omega$





1843 - 1921

The interative process (alternative or parallel) \rightsquigarrow On the disk \rightsquigarrow On Ω_2

$$\begin{cases} Lu_1^l = f \text{ on } \Omega_1 \\ u_1^l = g \text{ on } \partial\Omega \cap \partial\Omega_1 \\ \partial_n u_1^l + \Lambda u_1^l = \partial_n u_2^{l-1} + \Lambda u_2^{l-1} \text{ on } \Gamma \end{cases} \begin{cases} Lu_2^l = f \text{ on } \Omega_2 \\ u_2^l = g \text{ on } \partial\Omega \cap \partial\Omega_2 \\ \partial_n u_2^l + \Lambda u_2^l = \partial_n u_1^{l-1} + \Lambda u_1^{l-1} \text{ on } \Gamma \end{cases}$$

Convergence

• Convergence for $L = -\Delta$ by P.L. Lions in 1990 by energy estimates

The classical transmission operators

- Robin transmission : $\Lambda u = pu$
- Ventcell transmission : $\Lambda u = pu + q \partial_{\tau\tau}^2 u$

Numerical illustration-towards optimized parameters

Gander, Halpern, H. Krell MJPAA, 2021

Case of $-\operatorname{div}(\mathbb{A}\nabla u) = f$ with Robin BC and \mathbb{A} possibly anisotropic. **Deep influence of the choice of** p - Square mesh $h = 2^{-3}$



- \rightsquigarrow There exists an optimal choice p^{opt} for p!
- \rightsquigarrow The best parameter p^{opt} is strongly impacted by the anisotropy.

Numerical illustration-towards optimized parameters

Gander, Halpern, H. Krell MJPAA, 2021

Case of $-\operatorname{div}(\mathbb{A}\nabla u) = f$ with Robin BC and \mathbb{A} possibly anisotropic. **Deep influence of the choice of** p - influence of the mesh size



 \leadsto The best parameter is strongly impacted by the mesh size : $p^{opt} \sim C h^{-\frac{1}{2}}$

 \leadsto The convergence factor is strongly impacted by the mesh size : $\rho^{opt}\sim 1-Ch^{\frac{1}{2}}$

How can we estimate the optimal parameters for a general mesh?

1 Discrete Schwarz algorithm based on DDFV discretisation

- DDFV formalism
- DDFV Schwarz algorithm

2 Estimating the best parameters

- Optimization problem for the continuous problem
- Optimization problem for the discrete problem

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Classical finite volume strategy

The problem

$$-\operatorname{div}(\mathbb{A}\nabla u) = f$$
, on Ω , $u = 0$ on $\partial\Omega$

Main principle

• Let $\mathcal{T} = \bigcup K$ a partition of Ω . Associate a point x_K to each $K \in \mathcal{T}$.

■ Integrate on any control volume K the equation :

$$-\int_{\mathsf{K}} \operatorname{div}(\mathbb{A}\nabla u) \, dx = -\sum_{\sigma \in \partial_{\mathsf{K}}} \int_{\sigma} \mathbb{A}\nabla u \cdot \boldsymbol{n}_{\mathsf{K}\sigma} = \int_{\mathsf{K}} f(x) \, dx$$

- Approximate $\int_{\sigma} \mathbb{A} \nabla u \cdot \boldsymbol{n}_{\kappa\sigma}$ in a consistant and conservative way.
- ► Case $\mathbb{A} = Id$. Taylor expansion for $\sigma = \kappa | L$

$$m_{\sigma}rac{u(x_{ ext{L}})-u(x_{ ext{K}})}{d_{ ext{KL}}}\sim\int_{\sigma}
abla u\cdotm{ au}_{ ext{KL}} ext{ where }m{ au}_{ ext{KL}}=rac{x_{ ext{L}}ec{x}_{ ext{KL}}}{\|x_{ ext{L}}ec{x}_{ ext{K}}\|}$$

 \rightsquigarrow consistency requires orthogonality $oldsymbol{ au}_{ ext{KL}}=oldsymbol{n}_{ ext{K}\sigma}.$

 $\sigma \doteq K|L$

 x_{κ}

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• Case
$$\mathbb{A} = Id$$
 + orthogonality condition
 $\tau_{\text{KL}} = n_{\text{K}\sigma}$
 \rightsquigarrow FV4 scheme or TPFA scheme

If not, we need to approximate the gradient in another direction (*e.g.* $\tau_{K^*L^*}$). $\rightsquigarrow e.g.$ DDFV scheme that requires unknowns at both centers x_K and vertices x_{K^*} of the control volumes.



DDFV strategy for an elliptic problem

The problem

 $-\operatorname{div}\left(\mathbb{A}(z)\nabla u(z)\right) = f(z) \quad \text{in } \Omega + BC$

Main principle

- Consider a partition of Ω called **primal mesh**.
- Associate to each vertex a cell called **dual cell**.
- Integrate on both **primal cells** and **dual cells** the equation :

$$-\int_{\mathrm{c}} \operatorname{div}\left(\mathbb{A}(z)\nabla u(z)\right)\,dz = -\sum_{\sigma\in\partial\mathrm{c}}\int_{\sigma}\mathbb{A}(z)\nabla u\cdot\boldsymbol{n}_{\mathrm{c}\sigma} = \int_{\mathrm{c}}f(z)\,dz$$

- $\rightsquigarrow\,$ A natural way to approximate the divergence
 - Approximate the normal fluxes $\int_{\sigma} \mathbb{A}(z) \nabla u \cdot \boldsymbol{n}_{\mathrm{C}\sigma}$
 - Define a diamond cell around each edges of the meshes D = (x_K, x_{K*}, x_{L*}, x_L)
 - Taylor expansion to approximate ∇u on each D using $(u(x_{\text{K}}), u(x_{\text{L}}), u(x_{\text{K}^*}), u(x_{\text{L}^*}))$



Discrete operators

Discrete gradient : $\nabla^{\mathcal{D}} : \mathbb{R}^{\mathcal{T}} \to (\mathbb{R}^2)^{\mathcal{D}}$ defined by

$$abla_{
m D} u_{\mathcal{T}} = rac{1}{2m_{
m D}} \left((u_{
m L} - u_{
m K}) N_{
m KL} + (u_{
m L^*} - u_{
m K^*}) N_{
m K^* L^*}
ight).$$

$$\begin{split} & N_{\mathrm{KL}} = (x_{\mathrm{L}^*} - x_{\mathrm{K}^*})^{\perp} \\ & N_{\mathrm{K}^* \mathrm{L}^*} = -(x_{\mathrm{L}} - x_{\mathrm{K}})^{\perp} \\ & \nabla_{\mathrm{D}} u_{\mathcal{T}} \text{ is such that } \begin{cases} \nabla_{\mathrm{D}} u_{\mathcal{T}} \cdot (x_{\mathrm{L}} - x_{\mathrm{K}}) = u_{\mathrm{L}} - u_{\mathrm{K}}, \\ & \nabla_{\mathrm{D}} u_{\mathcal{T}} \cdot (x_{\mathrm{K}^*} - x_{\mathrm{L}^*}) = u_{\mathrm{K}^*} - u_{\mathrm{L}^*}. \end{cases} \end{split}$$

The discrete divergence $\operatorname{div}^{\mathcal{T}} : (\mathbb{R}^2)^{\mathcal{D}} \to \mathbb{R}^{\mathcal{T}}$ defined by

$$\operatorname{div}_{\scriptscriptstyle\mathrm{K}}(\xi_{\mathcal{D}}) := rac{1}{m_{\scriptscriptstyle\mathrm{K}}} \sum_{\scriptscriptstyle\mathrm{D}\in\mathcal{D}_{\scriptscriptstyle\mathrm{K}}} \xi_{\scriptscriptstyle\mathrm{D}} \cdot N_{\scriptscriptstyle\mathrm{KL}}, \, \operatorname{div}_{\scriptscriptstyle\mathrm{K}^*}(\xi_{\mathcal{D}}) := rac{1}{m_{\scriptscriptstyle\mathrm{K}^*}} \sum_{\scriptscriptstyle\mathrm{D}\in\mathcal{D}_{\scriptscriptstyle\mathrm{K}^*}} \xi_{\scriptscriptstyle\mathrm{D}} \cdot N_{\scriptscriptstyle\mathrm{K}^* {\scriptscriptstyle\mathrm{L}}^*}$$

Natural approx. of the divergence $\int_{\mathsf{K}} \operatorname{div}(\xi) = \sum_{\sigma = \mathsf{K} \mid \mathsf{L} \in \mathcal{D}_{\sigma}} \int_{\sigma} \xi(s) \cdot \boldsymbol{n}_{\mathsf{KL}}$!

Version for homogeneous Dirichlet BC

Lemma

For $u_{\mathcal{T}} \in \mathbb{R}^{\mathcal{T}}$ such that $u_{\partial \mathfrak{M}} = 0$ and $u_{\partial \mathfrak{M}^*} = 0$ and for $\xi_{\mathcal{D}} \in (\mathbb{R}^2)^{\mathcal{D}}$,

$$\left(\operatorname{div}^{\mathcal{T}} \xi_{\mathcal{D}}, u_{\mathcal{T}} \right) := \frac{1}{2} \sum_{\mathbf{k} \in \mathfrak{M}} m_{\mathbf{k}} \operatorname{div}_{\mathbf{k}}(\xi_{\mathcal{D}}) u_{\mathbf{k}} + \frac{1}{2} \sum_{\mathbf{k}^{*} \in \mathfrak{M}^{*}} m_{\mathbf{k}^{*}} \operatorname{div}_{\mathbf{k}^{*}}(\xi_{\mathcal{D}}) u_{\mathbf{k}^{*}}$$
$$= -\sum_{\mathbf{D} \in \mathcal{D}} m_{\mathbf{D}} \xi_{\mathbf{D}} \cdot \nabla_{\mathbf{D}} u_{\mathcal{T}} := -\int_{\Omega} \xi_{\mathcal{D}} \cdot \nabla^{\mathcal{D}} u_{\mathcal{T}}$$

A crucial tool to study the schemes!

DDFV meshes and unknowns

Primal, dual meshes (Left). Diamond meshes (Right)



Strategy

■ Integrate the equation on both primal and dual cells → a natural approximation of the divergence

Define an approximate gradient on the diamond cells $D \in \mathcal{D}$ Unknowns $(u_{\mathcal{T}}, \varphi_{\mathcal{T}}) \in \mathbb{R}^{\mathcal{T}} \times \mathbb{R}^{\partial \mathfrak{M}_{\Gamma}^*}$

- One unknown per cell (called **primal**) $u_{\mathfrak{M}} = (u_{\mathsf{K}})_{\mathsf{K} \in \mathfrak{M} \cup \partial \mathfrak{M}}$
- One unknown per vertex (called **dual**) $u_{\mathfrak{M}^*} = (u_{K^*})_{K^* \in \mathfrak{M}^* \cup \partial \mathfrak{M}^*}$
- Additionnal unknowns needed on $\partial \mathfrak{M}_{\Gamma}^*$

DDFV with mixed Robin or Ventcell/Dirichlet BC

Robin/Ventcell

 \rightarrow Equations for primal cells

Dirichlet

and interior dual cells

 \rightsquigarrow Equations for

exterior dual cells

- $\leadsto {\rm Dirichlet \ BC}$
- \rightsquigarrow Robin/Ventcell condition on primal boundary cells
- \rightsquigarrow Robin/Ventcell condition

on dual boundary cells

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Robin/Ventcell transmission condition

On each subdomain

- Choose $g^0_{\mathcal{T}_i}$.
- $\forall n \ge 0$, calculate

$$\mathcal{L}_{\Omega_j,\Gamma}^{\mathcal{T}_j}(u_{\mathcal{T}_j}^{l+1},\varphi_{\mathcal{T}_j}^{l+1},f_{\mathcal{T}_j},g_{\mathcal{T}_j}^l)=0$$

• Then evaluate $g_{\mathcal{T}_i}^{l+1}$ by

$$= 0.$$

P---

$$g_{j,\mathbf{L}}^{l+1} = -\frac{1}{m_{\sigma_{\mathbf{L}}}} \mathbb{A}^{\mathcal{D}} \nabla^{\mathcal{D}} u_{\mathcal{T}_{i}}^{l+1} \cdot N_{\mathbf{K}\mathbf{L}} + \Lambda^{\partial \mathfrak{M}_{i,j}} (u_{i}^{l+1})_{\mathbf{L}}, \forall \mathbf{L} \in \partial \mathfrak{M}_{j,\Gamma_{i}}$$
$$g_{j,\mathbf{K}^{*}}^{l+1} = -\frac{1}{m_{\sigma_{\mathbf{K}^{*}}}} \varphi_{i,\mathbf{K}^{*}}^{l+1} + \Lambda^{\partial \mathfrak{M}_{i,j}^{*}} (u_{i}^{l+1})_{\mathbf{K}^{*}}, \forall \mathbf{K}^{*} \in \partial \mathfrak{M}_{j,\Gamma_{i}}^{*}$$

 \rightsquigarrow Convergence of the algorithm proven by energy estimates

1 Discrete Schwarz algorithm based on DDFV discretisation

- DDFV formalism
- DDFV Schwarz algorithm

2 Estimating the best parameters

• Optimization problem for the continuous problem

• Optimization problem for the discrete problem

Assume that $\Omega = \Omega_1 \cup \Omega_2$ with $\Omega_1 = \mathbb{R}^- \times \mathbb{R}$ and $\Omega_2 = \mathbb{R}^+ \times \mathbb{R}$. Consider for $\Lambda u = pu$ or $\Lambda u = pu - q\partial_{yy}^2 u$ the problem

 $\rightsquigarrow \operatorname{On} \Omega_1 \qquad \qquad \rightsquigarrow \operatorname{On} \Omega_2$

$$\begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_{1}^{l}) + \eta u_{1}^{l} = 0 \text{ on } \Omega_{1} \\ u_{1}^{l} = 0 \text{ on } \partial\Omega \cap \partial\Omega_{1} \\ \partial_{n}u_{1}^{l} + \Lambda u_{1}^{l} = \partial_{n}u_{2}^{l-1} + \Lambda u_{2}^{l-1} \text{ on } \Gamma \end{cases} \begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_{2}^{l}) + \eta u_{2}^{l} = 0 \text{ on } \Omega_{2} \\ u_{2}^{l} = 0 \text{ on } \partial\Omega \cap \partial\Omega_{2} \\ \partial_{n}u_{2}^{l} + \Lambda u_{2}^{l} = \partial_{n}u_{1}^{l-1} + \Lambda u_{1}^{l-1} \text{ on } \Gamma \end{cases} \\ \\ \mathbf{Find} \ p^{opt} \ \mathbf{or} \ (p^{opt}, q^{opt}) \text{ that leads to the faster } u_{i}^{l} \xrightarrow{\rightarrow} 0. \end{cases}$$

Case Robin

Gander SIAM JNA, 2006

■ Case Ventcell

Gander, Halpern, H., Krell, MJPAA 2021

Assume that $\Omega = \Omega_1 \cup \Omega_2$ with $\Omega_1 = \mathbb{R}^- \times \mathbb{R}$ and $\Omega_2 = \mathbb{R}^+ \times \mathbb{R}$. Consider for $\Lambda u = pu$ or $\Lambda u = pu - q \partial_{yy}^2 u$ the problem

 \rightsquigarrow On Ω_1

 $\rightsquigarrow On \ \Omega_2$

$$\begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_1^l) + \eta u_1^l = 0 \text{ on } \Omega_1 \\ u_1^l = 0 \text{ on } \partial\Omega \cap \partial\Omega_1 \\ \partial_n u_1^l + \Lambda u_1^l = \partial_n u_2^{l-1} + \Lambda u_2^{l-1} \text{ on } \Gamma \end{cases} \begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_2^l) + \eta u_2^l = 0 \text{ on } \Omega_2 \\ u_2^l = 0 \text{ on } \partial\Omega \cap \partial\Omega_2 \\ \partial_n u_2^l + \Lambda u_2^l = \partial_n u_1^{l-1} + \Lambda u_1^{l-1} \text{ on } \Gamma \end{cases} \\ \text{Find } p^{opt} \text{ or } (p^{opt}, q^{opt}) \text{ that leads to the faster } u_i^l \xrightarrow{} 0. \\ \text{Method : Fourier transform in the } y \text{-direction leads for all } k \text{ to} \end{cases}$$

$$-A_{xx}\frac{\partial^2 \hat{u}_j^l}{\partial x^2} - 2ikA_{xy}\frac{\partial \hat{u}_j^l}{\partial x} + (\eta + k^2A_{yy})\hat{u}_j^l = 0 \quad + \quad BC$$

and looking for solutions on the form

$$\hat{u}_1^l(x,k) = C_1^l(k)e^{r_+(k)x}, \quad \hat{u}_2^l(x,k) = C_2^l(k)e^{r_-(k)x},$$

Results :

$$\begin{cases} C_j^l(k) = (\rho(P(k), k))^2 C_j^{l-2}(k), \ \rho(P, k) := \frac{P(k; p, q) - f(k^2)}{P(k; p, q) + f(k^2)} \\ P(k; p, q) = p + q A_{yy} k^2, \ f(k^2) = \sqrt{\eta A_{xx} + k^2 \det \mathbb{A}} \end{cases}$$

Assume that $\Omega = \Omega_1 \cup \Omega_2$ with $\Omega_1 = \mathbb{R}^- \times \mathbb{R}$ and $\Omega_2 = \mathbb{R}^+ \times \mathbb{R}$. Consider for $\Lambda u = pu$ or $\Lambda u = pu - q\partial_{uu}^2 u$ the problem

$\leadsto On \ \Omega_1$

 \rightsquigarrow On Ω_2

$$\begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_1^l) + \eta u_1^l = 0 \text{ on } \Omega_1 \\ u_1^l = 0 \text{ on } \partial\Omega \cap \partial\Omega_1 \\ \partial_n u_1^l + \Lambda u_1^l = \partial_n u_2^{l-1} + \Lambda u_2^{l-1} \text{ on } \Gamma \end{cases} \begin{cases} -\operatorname{div}(\mathbb{A}\nabla u_2^l) + \eta u_2^l = 0 \text{ on } \Omega_2 \\ u_2^l = 0 \text{ on } \partial\Omega \cap \partial\Omega_2 \\ \partial_n u_2^l + \Lambda u_2^l = \partial_n u_1^{l-1} + \Lambda u_1^{l-1} \text{ on } \Gamma \end{cases} \\ \\ \text{Find } p^{opt} \text{ or } (p^{opt}, q^{opt}) \text{ that leads to the faster } u_i^l \xrightarrow[l \to \infty]{} 0. \end{cases}$$

Results : The best parameter problem is reduced to an optimization problem on the form

$$\begin{cases} \text{Robin}: & \min_{(p)} \max_{\mu \in [\mu_{\min}, \mu_{\max}]} \left| \frac{p - f(\mu)}{p + f(\mu)} \right| \\ \text{Ventcell}: & \min_{(p,q)} \max_{\mu \in [\mu_{\min}, \mu_{\max}]} \left| \frac{p + qA_{yy}\mu - f(\mu)}{p + qA_{yy}\mu + f(\mu)} \right| \end{cases}$$

with $f(\mu) = \sqrt{\eta A_{xx} + \mu \det \mathbb{A}}$.

▶ From now on, we concentrate on the Robin case

Theorem

The optimization problem

$$p^{opt} = \operatorname{Argmin}\left(\sup_{\mu=[\mu_{\min},\mu_{\max}]} \left| \frac{p - f(\mu)}{p + f(\mu)} \right| \right),$$

admits a unique solution given by $p^{opt} = \sqrt{f(\mu_{max})f(\mu_{min})}$, and the associated convergence factor is

$$\rho^{opt} = \left| \frac{\sqrt{f(\mu_{\max})} - \sqrt{f(\mu_{\min})}}{\sqrt{f(\mu_{\max})} + \sqrt{f(\mu_{\min})}} \right|$$

Here, $f(\mu) = \sqrt{\eta A_{xx} + \mu \det \mathbb{A}}$, $\mu = k^2$, $k_{\min} = 1$, k_{\max} linked to the discretisation and the size of the domain.

$$\Rightarrow \begin{cases} p_{\infty}^{*} \sim \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^{2} \det A\right)^{\frac{1}{4}} \left(\pi \sqrt{\det A}\right)^{\frac{1}{2}} h_{y}^{-\frac{1}{2}} \\ \rho_{\infty}^{*} \sim 1 - 2 \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^{2} \det A\right)^{\frac{1}{4}} \left(\pi \sqrt{\det A}\right)^{-\frac{1}{2}} h_{y}^{\frac{1}{2}} \end{cases}$$

How is the convergence for general meshes for these parameters? **Example of meshes**



Numerical re	e <mark>sults</mark> (mesh size	$h_y =$	$\frac{1}{16}, k_{\rm max}$	$x = \frac{1}{h_{y}} -$	- 1)
--------------	------------------------	-----------	---------	-----------------------------	-------------------------	------

Best p	Best parameter type Continuous study				Numerical study						
Problem			SS	ts	tq	ss		ts		tq	
A_{xx}	A_{yy}	$p^*_{\infty, cvc}$	ρ	ρ	ρ	p*	ρ*	\check{p}^*	ρ*	\check{p}^*	ρ*
1	1	12.87	0.592	0.592	0.593	11.89	0.567	10.87	0.566	11.63	0.559
16	1	51.50	0.452	0.521	0.602	49.84	0.439	46.29	0.475	44.79	0.556
16	$\frac{1}{16}$	16.01	0.351	0.343	0.586	23.50	0.174	19.88	0.254	11.07	0.487
1	16	50.35	0.821	0.744	0.687	75.14	0.732	57.22	0.712	57.61	0.647
$\frac{1}{16}$	16	12.59	0.949	0.919	0.891	26.84	0.884	22.46	0.841	21.52	0.842

- $\rightsquigarrow\,$ Good performance for the Laplace operator
- $\rightsquigarrow\,$ Bad performance for anisotropic diffusion

Best parameters for infinite Cartesian grids

In the case of cartesian grids, for a diagonal operator, primal unknowns $(u_{m,n}^{j,l})$ and dual ones $(u_{m^*,n^*}^{j,l}, \psi_{n^*}^{j,l})$ are solution to two independant systems!

- j for the domain
- *l* for the iteration

- m or m^* for the horizontal position (in \mathbb{N})
- n or n^* for the vertical position (in $\{1, \dots, \frac{b}{h_y}\}$)



The two systems differ in the neighbourhood of $\Gamma = \partial \Omega_1 \cap \partial \Omega_2$ leading to **different optimal parameters**!

Best parameters for infinite Cartesian grids

Both families $(u_{m,n}^{j,l})$ and dual ones $(u_{m^*,n^*}^{j,l})$ solves the recursion like $\frac{A_{xx}}{h_x^2}(v_{m+1,n}-2v_{m,n}+v_{m-1,n})+\frac{A_{yy}}{h_y^2}(v_{m,n+1}-2v_{m,n}+v_{m,n-1})-\eta v_{m,n}=0$

Using Fourier expansion in the y-direction, we look for solution of the form

$$u_{m,n}^{j,\ell} = \sum_{k=1}^{k_{max}} \hat{u}_{m,k}^{j,\ell} \sin\left(k\pi n \frac{h_y}{b}\right), u_{m^*,n^*}^{j,\ell} = \sum_{k=1}^{k_{max}^*} \hat{u}_{m^*,k}^{j,\ell} \sin\left(k\pi n^* \frac{h_y}{b}\right)$$

with

$$\hat{u}_{m,k}^{j,\ell} = C^{j,\ell}(k)\lambda(k)^m, \quad \hat{u}_{m^*,k}^{j,\ell} = D^{j,\ell}(k)\lambda(k)^{m^*}$$

Transmission conditions leads to

$$C^{j,l} = \rho_{cc,\infty} C^{j,l-2}, \ D^{j,l} = \rho_{vc,\infty} D^{j,l-2}$$

where

$$\rho_{cc,\infty}(k;p) = \frac{p - f_{cc,\infty}(\nu(k))}{p + f_{cc,\infty}(\nu(k))}, \rho_{vc,\infty}(k;p) = \frac{p - f_{vc,\infty}(\nu(k))}{p + f_{vc,\infty}(\nu(k))}$$

with
$$\begin{cases} f_{cc,\infty}(\nu(k)) = 2\frac{A_{xx}}{h_x} \tanh\left(\frac{\nu(k)}{2}\right) \\ f_{vc,\infty}(\nu(k)) = \frac{A_{xx}}{h_x} \sinh\left(\nu(k)\right) \end{cases} \text{ and } \begin{cases} \lambda(k) := 1 + \frac{\mu(k)}{2} - \sqrt{\mu(k) + \frac{\mu(k)^2}{4}} < 1 \\ \mu(k) = \frac{h_x^2}{A_{xx}} \left(\frac{4A_{yy}}{h_y^2} \sin^2\left(\frac{k\pi hy}{2}\right) + \eta\right) \\ \nu(k) = -\ln(\lambda(k)) \end{cases}$$

Best parameters for infinite Cartesian grids

Optimization independently on primal and dual meshes

$$\begin{cases} p_{cc,\infty}^{opt} = \operatorname{Argmin}_{p} \left(\sup_{k=1,\cdots,k_{\max}} \left| \frac{p - f_{cc,\infty}(\nu(k))}{p + f_{cc,\infty}(\nu(k))} \right| \right) \\ p_{vc,\infty}^{opt} = \operatorname{Argmin}_{p} \left(\sup_{k=1,\cdots,k_{\max}^{*}} \left| \frac{p - f_{vc,\infty}(\nu(k))}{p + f_{vc,\infty}(\nu(k))} \right| \right) \end{cases}$$

with
$$k_{max} = \frac{b}{h_y}$$
 and $k_{max}^* := \frac{b}{h_y} - 1$

As in the continuous analysis

 $\frac{1}{\beta}$

1.5

1.0

$$\begin{cases} p_*^{opt} \sim \psi_*^{\frac{1}{2}} \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^2 \det A \right)^{\frac{1}{4}} \left(\pi \sqrt{\det A} \right)^{\frac{1}{2}} h_y^{-\frac{1}{2}} \\ \rho_*^{opt} \sim 1 - 2\psi_*^{-\frac{1}{2}} \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^2 \det A \right)^{\frac{1}{4}} \left(\pi \sqrt{\det A} \right)^{-\frac{1}{2}} h_y^{\frac{1}{2}} \end{cases}$$

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ó 50 100 150200250

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where $\beta := \frac{A_{yy}}{h_{yy}^2} \frac{h_x^2}{A_{xx}}$

Best parameters for bounded domain

Similar results for bounded cartesian grids $[-a, a] \times [0, b]$. Optimal parameters and convergence factors

$$\begin{cases} p_*^{opt} \sim \psi_*^{\frac{1}{2}} \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^2 \det A \right)^{\frac{1}{4}} \left(\pi \sqrt{\det A} \right)^{\frac{1}{2}} c^{\frac{1}{2}} h_y^{-\frac{1}{2}} \\ \rho_*^{opt} \sim 1 - 2\psi_*^{-\frac{1}{2}} \left(\eta A_{xx} + \left(\frac{\pi}{b}\right)^2 \det A \right)^{\frac{1}{4}} \left(\pi \sqrt{\det A} \right)^{-\frac{1}{2}} c^{\frac{1}{2}} h_y^{\frac{1}{2}} \end{cases}$$

with $c = \coth\left(\frac{a}{\sqrt{A_{xx}}} \sqrt{\eta + \left(\frac{\pi}{b}\right)^2 A_{yy}}\right).$



Best parameters for bounded Cartesian grids

How is the convergence for general meshes for these parameters?







Discrete study - bounded domain



- \leadsto For uniform meshes, the discrete study enable us to recover good convergence factors.
- \sim These optimal parameters performs relatively well for general meshes.
- \rightsquigarrow With adapted anisotropic meshes, we can use the continuous param.

Thank you for your attention!