



Advanced Domain Decomposition Methods

Parallel Schwarz Preconditioning and an Introduction to FROSch

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Part I — Classical Schwarz Domain Decomposition Methods



2. The Alt	ernating Schwarz Algorithm
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3. The Parallel Schwarz Algorithm

4. Comparison of the two Methods

5. Effect of the Size of the Overlap

1 Literature on Domain Decomposition Methods



Alfio Quarteroni and Alberto Valli

Domain decomposition methods for partial differential equations

Oxford University Press, 1999

📎 Barry Smith, Petter Bjorstad, and William Gropp Domain Decomposition: Parallel Multilevel Methods for Elliptic Partial Differential Equations

Cambridge University Press, 2004



📎 Andrea Toselli, and Olof Widlund

Domain decomposition methods-algorithms and theory.

Springer Science & Business Media, 2006



📎 Victorita Dolean, Pierre Jolivet, Frédéric Nataf An Introduction to Domain Decomposition Methods: Algorithms, Theory, and **Parallel Implementation**

Society for Industrial and Applied Mathematics, 2016

Domain Decomposition Methods



Graphics based on Heinlein, Perego, Rajamanickam (2022)

Idea

Decomposition of a large **global problem** into smaller **local problems**.





2 The Alternating Schwarz Algorithm

Historical remarks: The alternating Schwarz method is the earliest domain decomposition method (DDM), which has been invented by H. A. Schwarz and published in 1870:

- Schwarz used the algorithm to establish the **existence of harmonic functions** with prescribed boundary values on **regions with nonsmooth boundaries**.
- The regions are constructed recursively by forming unions of pairs of regions starting with "simple" regions for which existence can be established by more elementary means.
- At the core of Schwarz's work is a proof that **this iterative method converges in the maximum norm at a geometric rate**.



Classical "doorknob" geometry

$$(D_{1}) \begin{cases} -\Delta u^{n+1/2} = f & \text{in } \Omega_{1}', \\ u^{n+1/2} = u^{n} & \text{auf } \Gamma_{1} \\ u^{n+1/2} = u^{n} & \text{on } \Omega \setminus \overline{\Omega_{1}'} \end{cases}$$
$$(D_{2}) \begin{cases} -u^{n+1''} = f & \text{in } \Omega_{2}', \\ u^{n+1} = u^{n+1/2} & \text{auf } \Gamma_{2} \\ u^{n+1} = u^{n+1/2} & \text{on } \Omega \setminus \overline{\Omega_{2}'} \end{cases}$$



$$(D_{1}) \begin{cases} -\Delta u^{n+1/2} = f & \text{in } \Omega'_{1}, \\ u^{n+1/2} = u^{n} & \text{auf } \Gamma_{1} \\ u^{n+1/2} = u^{n} & \text{on } \Omega \setminus \overline{\Omega'_{1}} \end{cases}$$

$$D_{2} \begin{cases} -u^{n+2} &= r & \ln \Omega_{2}, \\ u^{n+1} &= u^{n+1/2} & \text{auf } \Gamma_{2} \\ u^{n+1} &= u^{n+1/2} & \text{on } \Omega \setminus \overline{\Omega_{2}'} \end{cases}$$

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For the sake of simplicity, instead of the two-dimensional geometry,



we consider the **one-dimensional Poisson** equation

-u'' = 1 in [0, 1], u(0) = u(1) = 0.

Domain decomposition:





$$-u'' = 1$$
, in [0,1], $u(0) = u(1) = 0$

We perform an alternating Schwarz iteration:



Figure 1: Iterate (left) and error (right) in iteration 0.

$$-u'' = 1$$
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Figure 1: Iterate (left) and error (right) in iteration 1.

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Figure 1: Iterate (left) and error (right) in iteration 2.

$$-u'' = 1$$
, in [0,1], $u(0) = u(1) = 0$

We perform an alternating Schwarz iteration:



Figure 1: Iterate (left) and error (right) in iteration 3.

$$-u'' = 1$$
, in [0,1], $u(0) = u(1) = 0$

We perform an alternating Schwarz iteration:



Figure 1: Iterate (left) and error (right) in iteration 4.

$$-u'' = 1$$
, in [0,1], $u(0) = u(1) = 0$

We perform an alternating Schwarz iteration:



Figure 1: Iterate (left) and error (right) in iteration 5.

The alternating Schwarz algorithm is **sequential** because **each local boundary value problem** depends on the solution of the **previous Dirichlet problem**:

$$(D_1) \begin{cases} -\Delta u^{n+1/2} = f & \text{in } \Omega'_1, \\ u^{n+1/2} = \mathbf{u}^n & \text{on } \partial \Omega'_1 \\ u^{n+1/2} = \mathbf{u}^n & \text{on } \Omega \setminus \overline{\Omega'_1} \end{cases}$$
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Idea: For all red terms, we **use the values from the previous iteration**. Then, the both Dirichlet problem **can be solved at the same time**.

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Idea: For all red terms, we **use the values from the previous iteration**. Then, the both Dirichlet problem **can be solved at the same time**.

3 The Parallel Schwarz Algorithm

The **parallel Schwarz algorithm** has been introduced by **Lions (1988)**. Here, we solve the local problems



Since u_1^n and u_2^n are both computed in the previous iteration, the problems can be solved independent of each other.

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Since u_1^n and u_2^n are both computed in the previous iteration, the problems can be solved independent of each other.

This method is suitable for **parallel computing**!



$$-u'' = 1$$
, in [0, 1], $u(0) = u(1) = 0$

We perform the **parallel Schwarz iteration**:



Figure 2: Iterate (left) and error (right) in iteration 0.

$$-u'' = 1$$
, in [0, 1], $u(0) = u(1) = 0$

We perform the **parallel Schwarz iteration**:



Figure 2: Iterate (left) and error (right) in iteration 1.

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, in [0, 1], $u(0) = u(1) = 0$

We perform the **parallel Schwarz iteration**:



Figure 2: Iterate (left) and error (right) in iteration 2.

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We perform the **parallel Schwarz iteration**:



Figure 2: Iterate (left) and error (right) in iteration 3.

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We perform the **parallel Schwarz iteration**:



Figure 2: Iterate (left) and error (right) in iteration 5.

Next, we compare the convergence of the two methods using the error plots:



Figure 3: Error in iteration 0.

Figure 4: Error in iteration 0.

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Figure 3: Error in iteration 2.

Figure 4: Error in iteration 4.

The alternating Schwarz method **converges twice as fast** as the parallel Schwarz method. However, the **local solutions** have to be computed **sequentially**.

5 Effect of the Size of the Overlap

We investigate the convergence of the methods (using the alternating method as an example) depending on the **size of the overlap**:




Figure 5: Error in iteration 0.



Figure 5: Error in iteration 1.



Figure 5: Error in iteration 2.



Figure 5: Error in iteration 3.



Figure 5: Error in iteration 4.



Figure 5: Error in iteration 5.



Figure 5: Error in iteration 5.

 \Rightarrow A larger overlap leads to faster convergence.

Part II — Schwarz Domain Decomposition Preconditioners



9. A Brief Overview Over the Theoretical Framework

10. Some Comments on Constructing Schwarz Preconditioners

6 Model Problem



Let us consider the simple diffusion model problem:

$$-\Delta u = f \quad \text{in } \Omega = [0, 1]^2,$$
$$u = 0 \quad \text{on } \partial \Omega.$$

Discretization using finite elements yields the linear equation system

$$Au = f$$
.





- Due to the local support of the finite element basis functions, the resulting system is sparse.
- However, due to the superlinear complexity and memory cost, the use of direct solvers becomes infeasible for fine meshes, that is, for the resulting large sparse equation systems.
- $\rightarrow\,$ We will employ iterative solvers:

For our elliptic model problem, the system matrix is symmetric positive definite, such that we can use the **preconditioner gradient descent (PCG) method**.

Goal - Numerical & Parallel (Weak) Scalability



 $\frac{\# \text{ degrees of freedom}}{\# \text{ processors}}$



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Preconditioned Conjugate Gradient (PCG) Method

Algorithm 1: Preconditioned conjugate gradient (PCG) method

Result: Approximate solution of the linear equation system Ax = b**Given:** Initial guess $\mathbf{x}^{(0)} \in \mathbb{R}^n$ and tolerance $\varepsilon > 0$ $r^{(0)} = h - Ax^{(0)}$ $\mathbf{p}^{(0)} := \mathbf{v}^{(0)} := \mathbf{M}^{-1} \mathbf{r}^{(0)}$ while $\|\boldsymbol{r}^{(k)}\| \ge \varepsilon \|\boldsymbol{r}^{(0)}\|$ do $\alpha_k := \frac{\left(\boldsymbol{p}^{(k)}, \boldsymbol{r}^{(k)}\right)}{\left(\boldsymbol{A}\boldsymbol{p}^{(k)}, \boldsymbol{p}^{(k)}\right)}$ $\mathbf{x}^{(k+1)} := \mathbf{x}^{(k)} + \alpha_k \mathbf{v}^{(k)}$ $\mathbf{r}^{(k+1)} := \mathbf{r}^{(k)} - \alpha_k \mathbf{A} \mathbf{p}^{(k)}$ $\mathbf{v}^{(k+1)} := \mathbf{M}^{-1} \mathbf{r}^{(k+1)}$ $eta_k := rac{ig(\mathbf{y}^{(k+1)}, \mathbf{A} \mathbf{p}^{(k)} ig)}{ig(\mathbf{p}^{(k)}, \mathbf{A} \mathbf{p}^{(k)} ig)}$ $p^{(k+1)} := r^{(k+1)} - \beta_k p^{(k)}$

end

Theorem 1

Let $A \in \mathbb{R}^{n \times n}$ be symmetric positive definite. Then the **PCG method** converges and the following error estimate holds:

$$\left\| \boldsymbol{e}^{(k)} \right\|_{\boldsymbol{A}} \leq 2 \left(\frac{\sqrt{\kappa \left(\boldsymbol{M}^{-1} \boldsymbol{A} \right)} - 1}{\sqrt{\kappa \left(\boldsymbol{M}^{-1} \boldsymbol{A} \right)} + 1} \right)^{k} \left\| \boldsymbol{e}^{(0)} \right\|_{\boldsymbol{A}}$$

where $\kappa \left(\mathbf{M}^{-1} \mathbf{A} \right) = \frac{\lambda_{\max} \left(\mathbf{M}^{-1} \mathbf{A} \right)}{\lambda_{\min} \left(\mathbf{M}^{-1} \mathbf{A} \right)}$ is condition number of the preconditioned matrix $\mathbf{M}^{-1} \mathbf{A}$.

Do we need a preconditioner?

The condition number of the stiffness matrix K for the diffusion problem behaves as follows:

$$\kappa\left(m{K}
ight) \leq Crac{\left(\max_{ au\in au_{h}}h_{ au}
ight)^{d}}{\left(\min_{ au\in au_{h}}h_{ au}
ight)^{d+2}} \stackrel{ ext{quasi uniform}}{\equiv} Crac{1}{h^{2}},$$

where τ_h is the triangulation and d is the problem dimension (for instance, d = 2, 3).

 \Rightarrow Convergence of the PCG method will deteriorate when refining the mesh.

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7 One-Level Overlapping Schwarz Preconditioners

Overlapping domain decomposition

As the classical alternating and parallel Schwarz method (overlapping) Schwarz preconditioners are based on overlapping decompositions of the computational domain

$$\Omega = \bigcup_{i=1}^{N} \Omega'_{i}.$$



Nonoverlap. DD

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Nonoverlap. DD





 $\mathsf{Overlap}\ \delta = 2h$



Based on an **overlapping domain decomposition**, we define an additive **one-level Schwarz preconditioner**

$$\boldsymbol{M}_{\text{OS-1}}^{-1} = \sum_{i=1}^{N} \boldsymbol{R}_{i}^{T} \boldsymbol{K}_{i}^{-1} \boldsymbol{R}_{i},$$

where \mathbf{R}_i and \mathbf{R}_i^T are restriction and prolongation operators corresponding to Ω'_i , and $\mathbf{K}_i := \mathbf{R}_i \mathbf{K} \mathbf{R}_i^T$. The \mathbf{K}_i correspond to **local Dirichlet problems** on the overlapping subdomains.

Condition number bound:

$$\kappa\left(\boldsymbol{M}_{\mathsf{OS-1}}^{-1}\boldsymbol{K}
ight)\leq C\left(1+rac{1}{H\delta}
ight)$$

where the constant C is independent of the subdomain size H and the width of the overlap δ .

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Solving a local subdomain problem



 \rightarrow Zero residual only inside this subdomain but particularly large residual inside the overlap.

Convergence of the PCG method with a one-level Schwarz preconditioner Initial guess Converged (13 its) **5 PCG iterations** 0.05 0.05 -1 -i 0.5 0.5 0.5 0.5 0.5 0.5 0 0 0 0 0 0 $\times 10^{-4}$ ×10⁻¹³ ×10⁻³ 10 2 5 0 -1 0.5 0.5 0.5 0.5 0.5 0.5 0 0 0 0 0 0

 \rightarrow Fast convergence of the preconditioned gradient decent (PCG) method (low number of subdomains).

8 Two-Level Overlapping Schwarz Preconditioners

Coarse triangulation

Nodal bilinear basis function



The additive two-level Schwarz preconditioner reads

$$\boldsymbol{M}_{\text{OS-2}}^{-1} = \underbrace{\boldsymbol{\Phi} \boldsymbol{K}_{0}^{-1} \boldsymbol{\Phi}^{T}}_{\text{coarse level - global}} + \underbrace{\sum_{i=1}^{N} \boldsymbol{R}_{i}^{T} \boldsymbol{K}_{i}^{-1} \boldsymbol{R}_{i}}_{\text{first level - local}},$$

where Φ contains the coarse basis functions and $K_0 := \Phi^T K \Phi$.

Condition number bound:

$$\kappa\left(\boldsymbol{M}_{\mathsf{OS-2}}^{-1}\boldsymbol{K}
ight)\leq C\left(1+rac{\boldsymbol{H}}{\delta}
ight)$$

where the constant *C* is **independent of** *h*, δ , and *H*; cf., e.g., **Toselli**, **Widlund** (2005).

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ight)\leq C\left(1+rac{\boldsymbol{H}}{\delta}
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where the constant C is independent of h, δ , and H; cf., e.g., Toselli, Widlund (2005).

One- Vs Two-Level Schwarz Preconditioners

Diffusion model problem in two dimensions, # subdomains = # cores, H/h = 100



ightarrow We only obtain numerical scalability if a coarse level is used.

 \rightarrow Convergence is **faster** for **larger overlaps**.

One- Vs Two-Level Schwarz Preconditioners

Diffusion model problem in two dimensions, # subdomains = # cores, H/h = 100



 \rightarrow We only obtain **numerical scalability** if a **coarse level** is used.

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One- Vs Two-Level Schwarz Preconditioners

Diffusion model problem in two dimensions, # subdomains = # cores, H/h = 100



- \rightarrow We only obtain numerical scalability if a coarse level is used.
- \rightarrow Convergence is **faster** for **larger overlaps**.

9 A Brief Overview Over the Theoretical Framework

In order to establish a condition number bound for $\kappa \left(M_{ad}^{-1} K \right)$ based on the **abstract Schwarz framework**, we have to verify the following **three assumptions**:

Assumption 1: Stable Decomposition

There exists a constant C_0 such that, for every $u \in V$, there exists a decomposition $u = \sum_{i=0}^{N} R_i^T u_i$, $u_i \in V_i$, with

$$\sum_{i=0}^N \mathsf{a}_i(u_i,u_i) \leq C_0^2 \mathsf{a}(u,u).$$

Assumption 2: Strengthened Cauchy-Schwarz Inequality

There exist constants $0 \le \epsilon_{ij} \le 1$, $1 \le i, j \le N$, such that

$$\left| \mathsf{a}(\mathsf{R}_{i}^{\mathsf{T}}\mathsf{u}_{i},\mathsf{R}_{j}^{\mathsf{T}}\mathsf{u}_{j}) \right| \leq \epsilon_{ij} \left(\mathsf{a}(\mathsf{R}_{i}^{\mathsf{T}}\mathsf{u}_{i},\mathsf{R}_{i}^{\mathsf{T}}\mathsf{u}_{i}) \right)^{1/2} \left(\mathsf{a}(\mathsf{R}_{j}^{\mathsf{T}}\mathsf{u}_{j},\mathsf{R}_{j}^{\mathsf{T}}\mathsf{u}_{j}) \right)^{1/2}$$

for $u_i \in V_i$ and $u_j \in V_j$. (Consider $\mathcal{E} = (\varepsilon_{ij})$ and $\rho(\mathcal{E})$ its spectral radius)

Assumption 3: Local Stability

There exists $\omega < 0$, such that

$$a(R_i^T u_i, R_i^T u_i) \le \omega a_i(u_i, u_i), \quad u_i \in range(\tilde{P}_i), \quad 0 \le i \le N.$$

General Condition Number Bound

With Assumption 1-3, we have

$$\kappa\left(M_{\mathrm{ad}}^{-1}K\right) \leq C_{0}^{2}\omega\left(\rho\left(\varepsilon\right)+1\right)$$

for

$$M_{\mathrm{ad}}^{-1} = \sum_{i=0/1}^{N} R_i^{\mathsf{T}} K_i^{-1} R_i;$$

see, e.g., Toselli, Wildund (2005).

To obtain a condition number bound for a specific additive Schwarz preconditioner, we have to bound ω , $\rho(\mathcal{E})$, and C_0^2 .

The constants ω and $\rho(\mathcal{E})$ can often be handled easily.

Exact Solvers

If we choose the local bilinear forms as

$$a_i(u_i, u_i) := a(R_i^T u_i, R_i^T u_i)$$

we obtain $K_i = R_i K R_i^T$ and $\omega = 1$. \rightarrow For exact **exact local and coarse solvers**, ω does not depend on the coefficient.

Coloring Constant



The spectral radius $\rho(\mathcal{E})$ is bounded by the number of colors N^c of the domain decomposition.

 $\rightarrow N^c$ depends only on the domain decomposition but not on the coefficient function.

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Assumption 3 is typically proved by constructing functions $u_i \in V_i$, i = 0, ..., N, such that

$$u = \sum_{i=0}^{N} R_i^{\mathsf{T}} u_i$$
 and $\sum_{i=0}^{N} \mathsf{a}_i(u_i, u_i) \leq C_0^2 \mathsf{a}(u, u)$

for any given function $u \in V$. Let us sketch the difference between the one- and two-level preconditioners.

One-level Schwarz preconditioner

During the proof of the condition number, we have to use an L^2 -norm using Friedrich's inequality globally on Ω :

$$\sum_{i=1}^{N} \|u\|_{L_{2}(\Omega_{i})}^{2} = \|u\|_{L_{2}(\Omega)}^{2} \leq C |u|_{H^{1}(\Omega)}^{2},$$

This results in

$$\sum_{i=1}^{N} a_i\left(u_i, u_i\right) \leq C\left(1 + \frac{H}{\delta}\right) a\left(u, u\right) + C\frac{1}{H\delta}a\left(u, u\right)$$

Since $\frac{H}{\delta} \leq \frac{1}{H\delta}$, we obtain

$$\sum_{i=1}^{N} a_i\left(u_i, u_i\right) \leq C\left(1 + \frac{1}{H\delta}\right) a\left(u, u\right).$$

Two-level Schwarz preconditioner

In contrast to the one-level method, we can estimate the L^2 -norm locally since we instead have the term $u - u_0$

$$\sum_{i=1}^{N} \|u - u_0\|_{L_2(\Omega'_i)}^2 \leq \sum_{i=1}^{N} CH^2 |u|_{H^1(\omega_{\Omega_i})}^2.$$

Different from the one-level preconditioner, we obtain an H^2 term in the final estimate:

$$\sum_{i=1}^{N} a_i\left(u_i, u_i\right) \leq C\left(1 + \frac{H}{\delta}\right) a\left(u, u\right) + C\frac{1}{H\delta}\mathsf{H}^2 a\left(u, u\right)$$
$$\leq C\left(1 + \frac{\mathsf{H}}{\delta}\right) a\left(u, u\right)$$

10 Some Comments on Constructing Schwarz Preconditioners

Restricted Schwarz Preconditioner (Cai and Sarkis (1999))

Replace the prolongation \boldsymbol{R}_i^T by $\boldsymbol{\tilde{R}}_i^T$,

$$\boldsymbol{M}_{\text{OS-1}}^{-1} = \sum_{i=1}^{N} \widetilde{\boldsymbol{R}}_{i}^{T} \boldsymbol{K}_{i}^{-1} \boldsymbol{R}_{i}$$

where

$$\sum_{i=1}^{N} \widetilde{R}_{i}^{T} = I.$$

Therefore, we can just introduce a diagonal scaling matrix \boldsymbol{D} , such that

$$\widetilde{\boldsymbol{R}}_i^T = \boldsymbol{D} \boldsymbol{R}_i^T,$$

for example based on a nonoverlapping domain decomposition or an inverse multiplicity scaling.

This often **improves the convergence**, however, the preconditioner becomes **unsymmetric**.





Changing the local and coarse solvers

For solving

$$\mathbf{K}_i^{-1}, \quad i=0,\ldots,N,$$

we can employ inexact solvers instead of direct solvers, such as

- iterative solvers
- preconditioners

to **speedup the computing times**. Of course, **convergence might slow down** a bit a the same time.

Choose another coarse basis

As it turns out, the choice of a **suitable coarse basis** is one of the more important ingredients for a **scalable and robust domain decomposition solver**.

We will discuss this again in a few slides.



Part III — Schwarz Domain Decomposition Preconditioners in FROSch

11.	Wishlist for a Parallel Schwarz Preconditioning Package
12.	$\rm FROSch$ (Fast and Robust Overlapping Schwarz) Framework in $\rm Trillinos$
13.	Algorithmic Framework for FROSch Coarse Spaces
14.	Examples of $FROSCH$ Coarse Spaces
15.	Some Numerical Results
16.	Exercises

11 Wishlist for a Parallel Schwarz Preconditioning Package

Parallel distributed system

$$Ax = b$$

with



Wishlist:

- Parallel scalability (includes numerical scalability)
- Usability \rightarrow **algebraicity**
- Generality
- Robustness



12 FROSch (Fast and Robust Overlapping Schwarz) Framework in Trilinos





Software

- Object-oriented C++ domain decomposition solver framework with $\rm MPI\text{-}based$ distributed memory parallelization
- Part of TRILINOS with support for both parallel linear algebra packages EPETRA and TPETRA
- Node-level parallelization and performance portability on CPU and GPU architectures through KOKKOS and KOKKOSKERNELS
- Accessible through unified ${\rm TRILINOS}$ solver interface ${\rm STRATIMIKOS}$

Methodology

- Parallel scalable multi-level Schwarz domain decomposition
 preconditioners
- Algebraic construction based on the parallel distributed system matrix
- Extension-based coarse spaces

Team (active)

- Alexander Heinlein (TU Delft)
- Siva Rajamanickam (Sandia)
- Friederike Röver (TUBAF)
- Axel Klawonn (Uni Cologne)
- Oliver Rheinbach (TUBAF)
- Ichitaro Yamazaki (Sandia)

Algorithmic Framework for FROSch Overlapping Domain Decompositions

Overlapping domain decomposition

In FROSCH, the overlapping subdomains $\Omega'_1, ..., \Omega'_N$ are constructed by **recursively adding layers of elements** to the nonoverlapping subdomains; this can be performed based on the sparsity pattern of K.



Nonoverlapping DD
Algorithmic Framework for FROSch Overlapping Domain Decompositions

Overlapping domain decomposition

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Nonoverlapping DD



Algorithmic Framework for FROSch Overlapping Domain Decompositions

Overlapping domain decomposition

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Nonoverlapping DD



 $\text{Overlap } \delta = 1h$



 $\mathsf{Overlap}\ \delta = 2h$

Algorithmic Framework for FROSch Overlapping Domain Decompositions

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In FROSCH, the overlapping subdomains $\Omega'_1, ..., \Omega'_N$ are constructed by **recursively adding layers of elements** to the nonoverlapping subdomains; this can be performed based on the sparsity pattern of K.



Nonoverlapping DD



Overlap $\delta = 1h$



Overlap $\delta = 2h$

Computation of the overlapping matrices

The overlapping matrices

$$oldsymbol{K}_i = oldsymbol{R}_i oldsymbol{K} oldsymbol{R}_i^T$$

can easily be extracted from K since R_i is just a global-to-local index mapping.

1. Identification interface components



Identification from parallel distribution of matrix:



Alexander Heinlein (TU Delft)





3. Interface basis

 null space basis

 (e.g., linear elasticity: translations, linearized rotation(s))

 ×

The interface values of the basis of the coarse space is obtained by **multiplication with the null space**.

2. Interface partition of unity (IPOL vertex & edge functions vertex functions





Based on the interface components, construct an **interface partition of** unity:

$$\sum_i \pi_i = 1$$
 on Γ



4. Extension into the interior

edge basis function

vertex basis function



The values in the interior of the subdomains are computed via the **extension operator**:

$$\Phi = \begin{bmatrix} \Phi_I \\ \Phi_{\Gamma} \end{bmatrix} = \begin{bmatrix} -\kappa_{II}^{-1}\kappa_{\Gamma I}^{T}\Phi_{\Gamma} \\ \Phi_{\Gamma} \end{bmatrix}.$$

(For elliptic problems: energy-minimizing extension)

1. Identification interface components



Identification from parallel distribution of matrix:



3. Interface basis



I he interface values of the basis of the coarse space is obtained by **multiplication with the null space**.

2. Interface partition of unity (IPOU)

vertex & edge functions



vertex functions

Based on the interface components, construct an interface partition of unity:

$$\sum\nolimits_{i} \pi_{i} = 1 \,\, {
m on} \,\, {
m \Gamma}$$



4. Extension into the interior

edge basis function



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(For elliptic problems: energy-minimizing extension)

Alexander Heinlein (TU Delft)





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(For elliptic problems: energy-minimizing extension)

Alexander Heinlein (TU Delft)





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14 Examples of FROSch Coarse Spaces

GDSW (Generalized Dryja-Smith-Widlund)





- Dohrmann, Klawonn, Widlund (2008)
- Dohrmann, Widlund (2009, 2010, 2012)

MsFEM (Multiscale Finite Element Method)





- Hou (1997), Efendiev and Hou (2009)
- Buck, Iliev, and Andrä (2013)
- H., Klawonn, Knepper, Rheinbach (2018)

RGDSW (Reduced dimension GDSW)





- Dohrmann, Widlund (2017)
- H., Klawonn, Knepper, Rheinbach, Widlund (2022)

Q1 Lagrangian / piecewise bilinear





Piecewise linear interface partition of unity functions and a **structured domain decomposition**.

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Weak Scalability up to 64 k MPI ranks / 1.7 b Unknowns (3D Poisson; Juqueen)



Two-level vs three-level GDSW

Heinlein, Klawonn, Rheinbach, Röver (2019, 2020).



Alexander Heinlein (TU Delft)

Exemplary Applications



16 Exercises

All the material for the exercises of this session can be found in the folder lab2 of the **GitHub repository** of the summer school: https://github.com/jthies/dcse-summerschool

Important are the last two exercises

- exercise 3 Implementing a One-Level Schwarz Preconditioner Using $\mathrm{FROS}_{\mathrm{CH}}$
- exercise 4 Implementing a GDSW Preconditioner Using ${\rm FROS}_{\rm CH}$

and the corresponding solutions (in the subfolder solution),

Each exercise has two parts:

- 1. Implement the missing code; step-by-step explanations in the README.md files.
- 2. Perform numerical experiments to investigate the behavior of the methods.

Parallelization

The code assumes a **one-to-one correspondence of MPI ranks and subdomains**. In order to run with > 1 subdomains, you have to increase the number of MPI ranks. For instance, for 4 MPI ranks / subdomains: mpirun -n 4 ./main.x

Thank you for your attention! Questions?

 $\label{eq:Want to try out FROSch at home?} \\ \rightarrow \mbox{https://github.com/searhein/frosch-demo for a demo with simple installation via Docker.}$