

IDR(s)

**A family of simple and fast algorithms
for solving large nonsymmetric
systems of linear equations**

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Outline

- Introduction
- The Induced Dimension Reduction Theorem
- The IDR(s) algorithm
- Numerical experiments
- Conclusions

Product Bi-CG methods

Bi-CG solves nonsymmetric linear systems using (short) CG recursions but needs extra matvec with A^H .

Idea of Sonneveld: use 'wasted' matvec in a more useful way.

Result: transpose-free methods:

- CGS (Sonneveld, 1989)
- Bi-CGSTAB (Van der Vorst, 1992)
- BiCGSTAB2 (Gutknecht, 1993)
- TFQMR (Freund, 1993)
- BiCGstab(ℓ) (Sleijpen and Fokkema, 1994)
- Many other variants

Historical remarks

Sonneveld first developed IDR (1980).

Analysis showed that IDR was Bi-CG combined with linear minimal residual steps.

The fact that IDR is transpose free, combined with the relation with Bi-CG led to the development of a now famous algorithm: CGS.

Later Van der Vorst proposed another famous method: Bi-CGSTAB, which is mathematically equivalent with IDR.

As a result of these developments, the basic IDR idea was abandoned for the Bi-CG approach. IDR is now forgotten.

The IDR idea

The IDR-idea is to generate a sequence of subspaces $\mathcal{G}_0 \cdots \mathcal{G}_j$ with the following operations:

- Intersect \mathcal{G}_{j-1} with fixed subspace \mathcal{S} ,
- Compute $\mathcal{G}_j = (\mathbf{I} - \omega_j \mathbf{A})(\mathcal{G}_{j-1} \cap \mathcal{S})$.

The subspaces $\mathcal{G}_0 \cdots \mathcal{G}_j$ are nested and of shrinking dimension.

The IDR theorem

Theorem 1 (IDR) *Let A be any matrix in $\mathbb{C}^{N \times N}$, let v_0 be any nonzero vector in \mathbb{C}^N , and let \mathcal{G}_0 be the complete Krylov space $\mathcal{K}^N(A, v_0)$. Let \mathcal{S} denote any (proper) subspace of \mathbb{C}^N such that \mathcal{S} and \mathcal{G}_0 do not share a nontrivial invariant subspace of A , and define the sequence \mathcal{G}_j , $j = 1, 2, \dots$ as*

$$\mathcal{G}_j = (\mathbf{I} - \omega_j \mathbf{A})(\mathcal{G}_{j-1} \cap \mathcal{S})$$

where the ω_j 's are nonzero scalars. Then

- (i) $\mathcal{G}_j \subset \mathcal{G}_{j-1}$ for all $j > 0$.*
- (ii) $\mathcal{G}_j = \{\mathbf{0}\}$ for some $j \leq N$.*

Making an IDR algorithm

The IDR theorem can be used to construct solution algorithms.

This is done by constructing residuals $r_n \in \mathcal{G}_j$.

According to the IDR theorem ultimately $r_n \in \mathcal{G}_M = \{\mathbf{0}\}$.

In order to generate residuals and corresponding solution approximations we first look at the basic recursions.

Krylov methods: basic recursion (1)

A Krylov-type solver produces iterates x_n , for which the residuals $r_n = b - Ax_n$ are in the Krylov spaces

$$\mathcal{K}^n(\mathbf{A}, \mathbf{r}_0) = \mathbf{r}_0 \oplus \mathbf{A}\mathbf{r}_0 \oplus \mathbf{A}^2\mathbf{r}_0 \oplus \cdots \oplus \mathbf{A}^n\mathbf{r}_0 ,$$

The next residual r_{n+1} can be generated by

$$\mathbf{r}_{n+1} = -\alpha\mathbf{A}\mathbf{r}_n + \sum_{j=0}^{\hat{j}} \beta_j \mathbf{r}_{n-j} .$$

The parameters α, β_j determine the specific method and must be such that x_{n+1} can be computed.

Krylov methods: basic recursion (2)

By using the difference vector

$$\Delta \mathbf{r}_k = \mathbf{r}_{k+1} - \mathbf{r}_k = -\mathbf{A}(\mathbf{x}_{n+1} - \mathbf{x}_n),$$

an explicit way to satisfy this requirement is

$$\mathbf{r}_{n+1} = \mathbf{r}_n - \alpha \mathbf{A} \mathbf{r}_n - \sum_{j=1}^{\hat{j}} \gamma_j \Delta \mathbf{r}_{n-j},$$

which leads to the following update for the \mathbf{x} estimate:

$$\mathbf{x}_{n+1} = \mathbf{x}_n + \alpha \mathbf{r}_n - \sum_{j=1}^{\hat{j}} \gamma_j \Delta \mathbf{x}_{n-j},$$

Computation of a new residual (1)

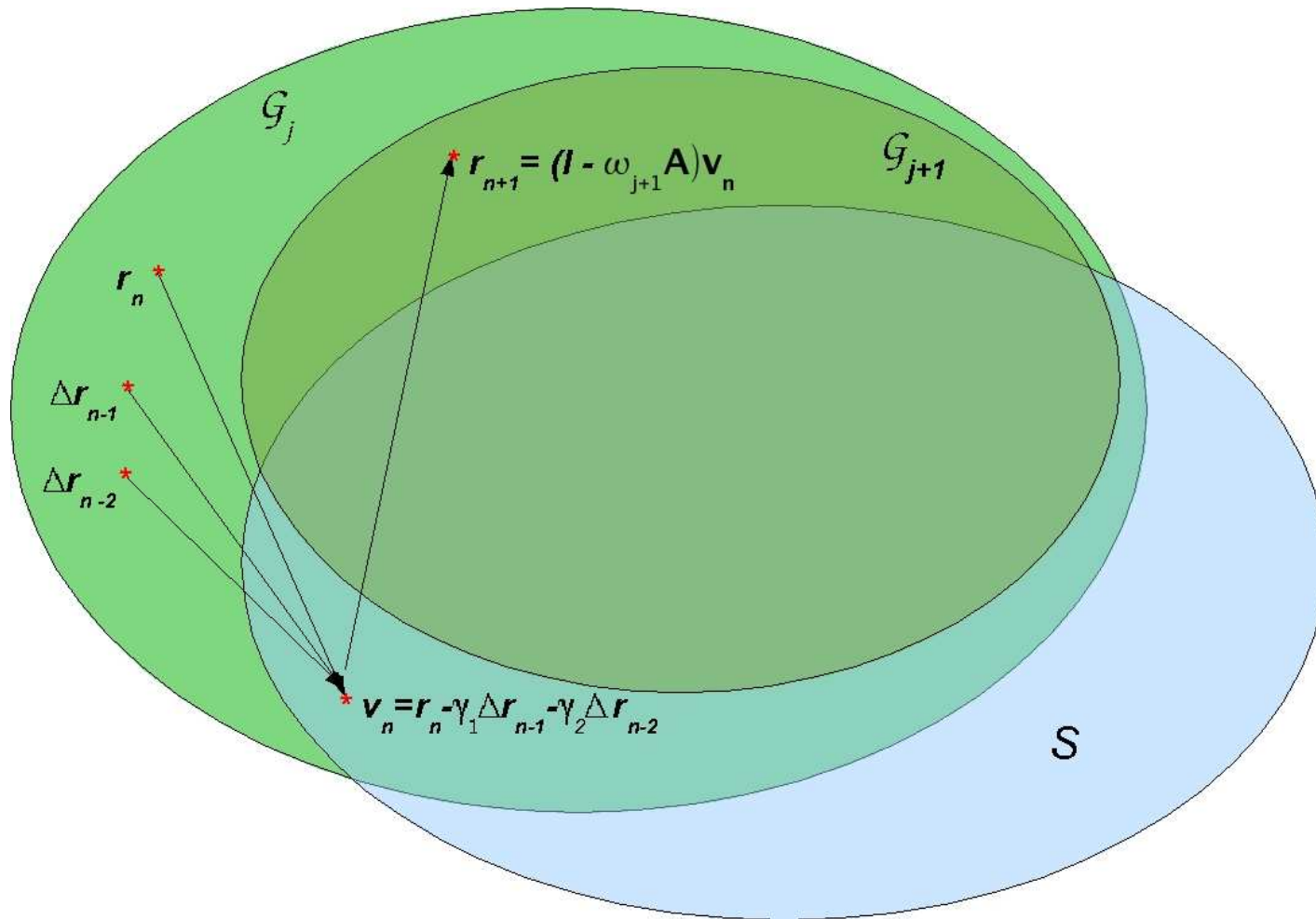
Residuals are computed that are forced to be in the subspaces \mathcal{G}_j , by application of the IDR-theorem.

The residual r_{n+1} is in \mathcal{G}_{j+1} if

$$r_{n+1} = (\mathbf{I} - \omega_{j+1}\mathbf{A})v \quad \text{with } v \in \mathcal{G}_j \cap \mathcal{S} .$$

The main problem is to find v .

Computation of a new residual (2)



Computation of a new residual (3)

The vector v is a combination of the residuals r_l in \mathcal{G}_j .

$$v = r_n - \sum_{j=1}^{\hat{j}} \gamma_j \Delta r_{n-j} .$$

Let the space \mathcal{S} be the left null space of some $N \times s$ matrix P :

$$P = (p_1 \ p_2 \ \dots \ p_s), \quad \mathcal{S} = \mathcal{N}(P^H) .$$

Since v is also in $\mathcal{S} = \mathcal{N}(P^H)$, it must satisfy

$$P^H v = 0 .$$

Combining these two yields an $s \times \hat{j}$ linear system for the coefficients γ_j that (normally) is uniquely solvable if $\hat{j} = s$.

Computation of a new residual (4)

Hence with the residual r_n , and a matrix ΔR consisting of the last s residual differences:

$$\Delta R = (\Delta r_{n-1} \quad \Delta r_{n-2} \quad \dots \quad \Delta r_{n-s})$$

a suitable v can be found by

Solve $s \times s$ system $(P^H \Delta R)c = P^H r_n$

Calculate $v = r_n - \Delta R c$

Building \mathcal{G}_{j+1} (1)

Assume \mathbf{r}_n and all columns of $\Delta \mathbf{R}$ are in \mathcal{G}_j , and let \mathbf{r}_{n+1} be calculated as

$$\mathbf{r}_{n+1} = \mathbf{v} - \omega_{j+1} \mathbf{A} \mathbf{v}$$

Then $\mathbf{r}_{n+1} \in \mathcal{G}_{j+1}$.

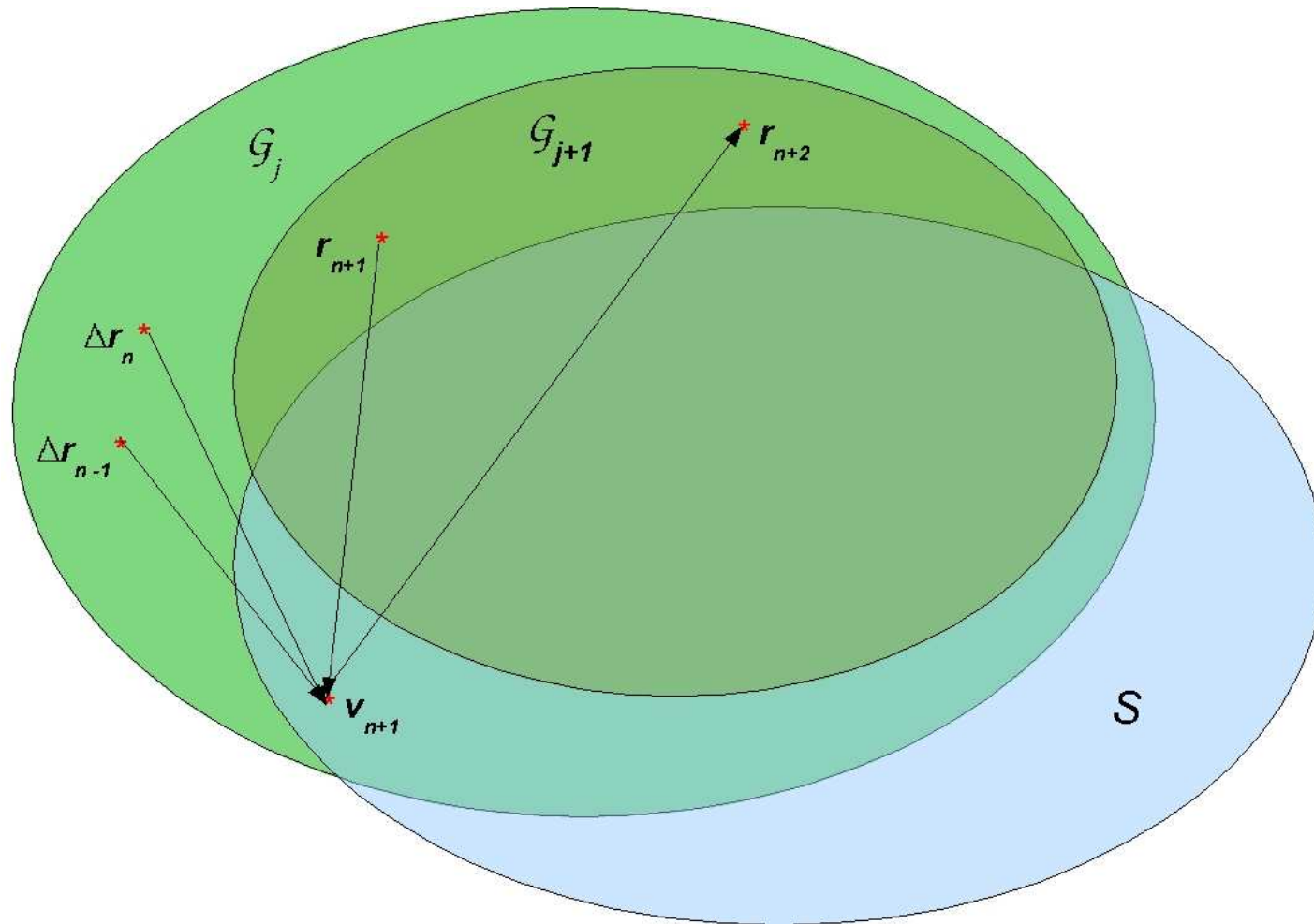
Since $\mathcal{G}_{j+1} \subset \mathcal{G}_j$ (theorem) we automatically have

$$\mathbf{r}_{n+1} \in \mathcal{G}_j$$

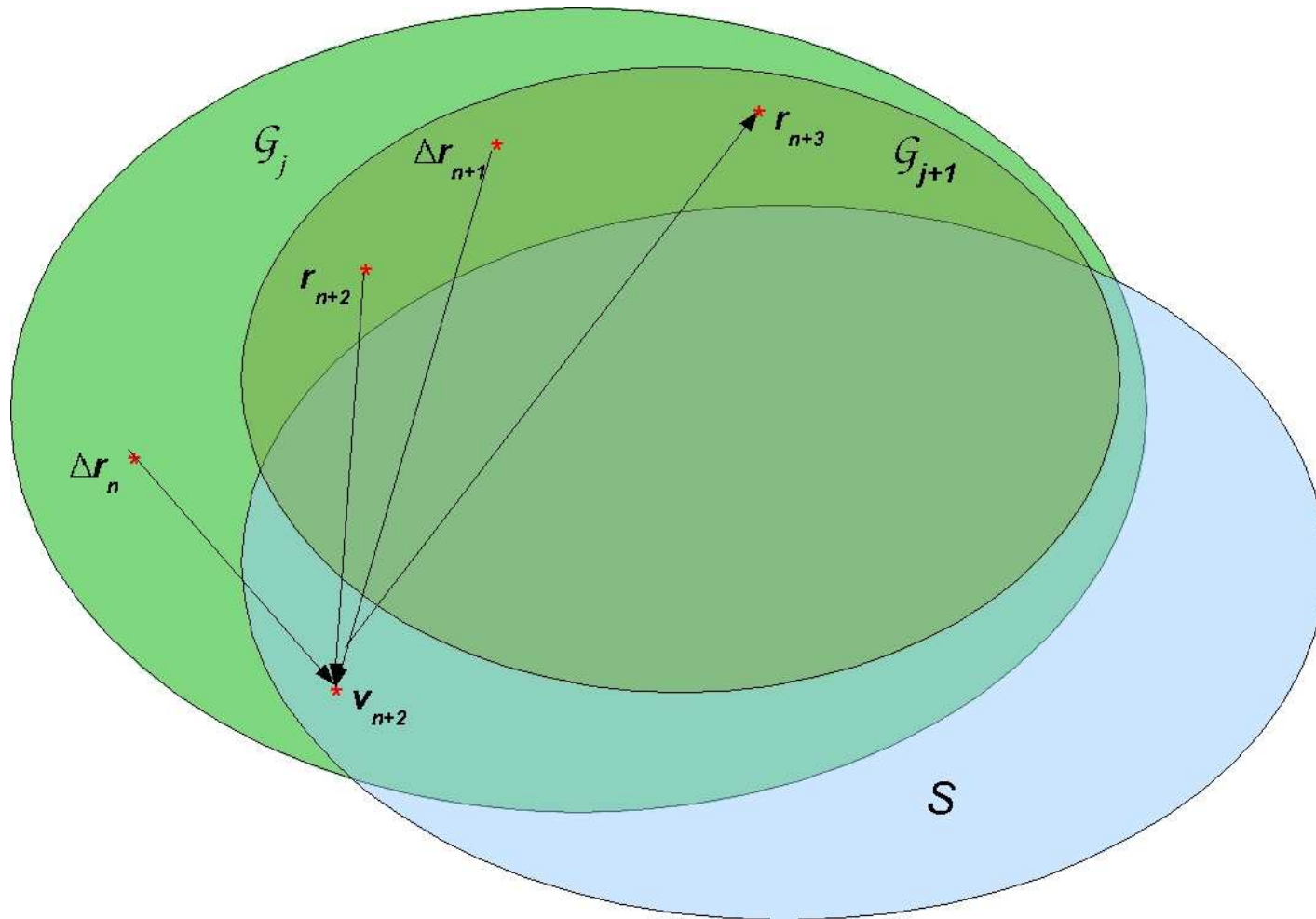
Now the next $\Delta \mathbf{R}$ is made by repeating the calculations.

In this way we find $s + 1$ residuals in \mathcal{G}_{j+1}

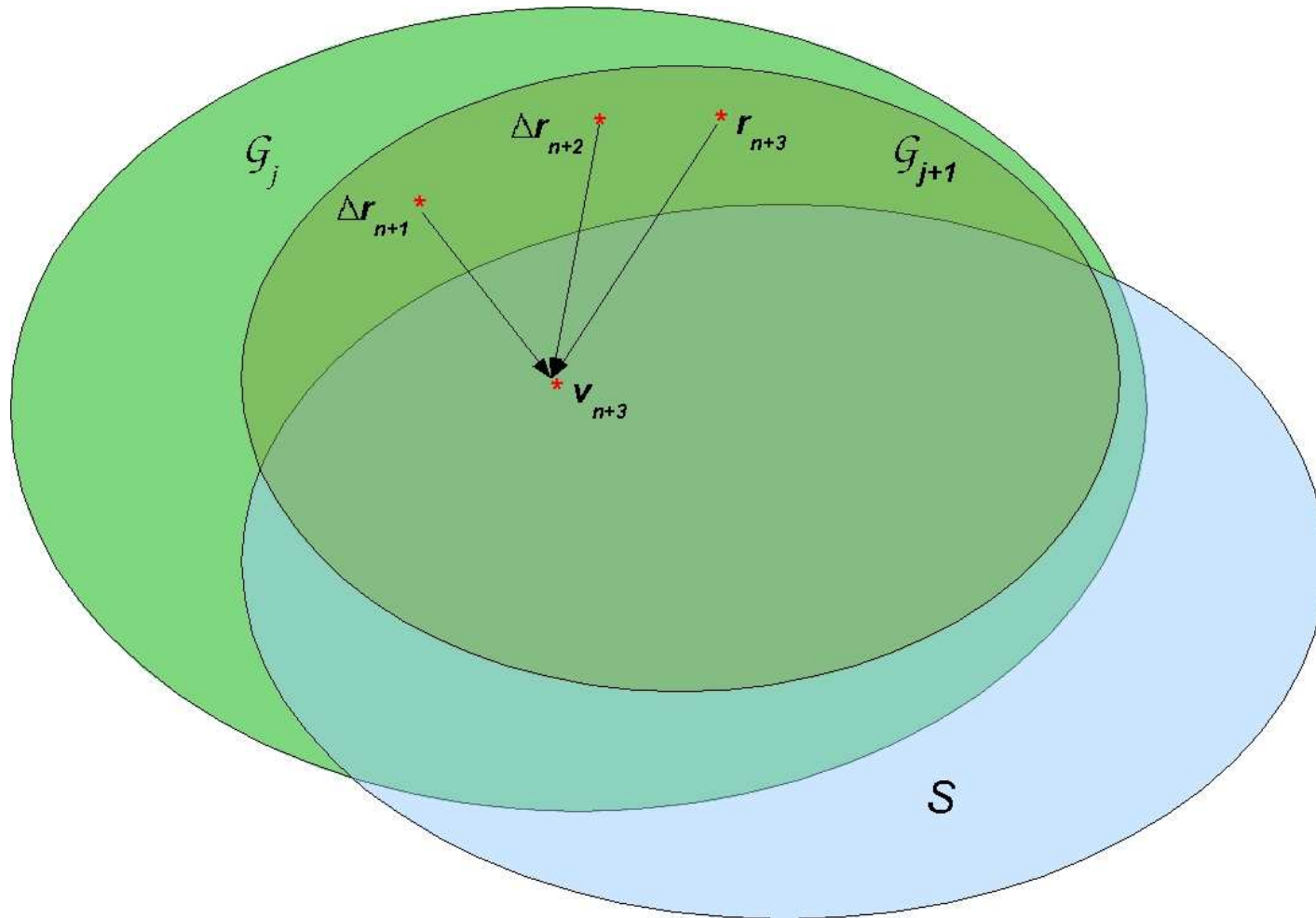
Building \mathcal{G}_{j+1} (2)



Building \mathcal{G}_{j+1} (3)



Building \mathcal{G}_{j+1} (4)



A few details

1. The first $s + 1$ residuals, starting with r_0 can be constructed by any Krylov-based iteration, such as a local minimum residual method.
2. In our actual implementation, all steps are identical. However, in calculating the first residual in \mathcal{G}_{j+1} , a new value ω_{j+1} may be chosen. We choose ω_{j+1} such that $\|v - \omega_{j+1}Av\|$ is minimal.

Basic IDR(s) algorithm.

while $\|\mathbf{r}_n\| > TOL$ or $n < MAXIT$ **do**

for $k = 0$ to s **do**

Solve \mathbf{c} from $\mathbf{P}^H d\mathbf{R}_n \mathbf{c} = \mathbf{P}^H \mathbf{r}_n$

$\mathbf{v} = \mathbf{r}_n - d\mathbf{R}_n \mathbf{c}; \mathbf{t} = \mathbf{A}\mathbf{v};$

if $k = 0$ **then**

$$\omega = (\mathbf{t}^H \mathbf{v}) / (\mathbf{t}^H \mathbf{t});$$

end if

$d\mathbf{r}_n = -d\mathbf{R}_n \mathbf{c} - \omega \mathbf{t}; d\mathbf{x}_n = -d\mathbf{X}_n \mathbf{c} + \omega \mathbf{v};$

$\mathbf{r}_{n+1} = \mathbf{r}_n + d\mathbf{r}_n; \mathbf{x}_{n+1} = \mathbf{x}_n + d\mathbf{x}_n;$

$n = n + 1;$

$d\mathbf{R}_n = (d\mathbf{r}_{n-1} \cdots d\mathbf{r}_{n-s}); d\mathbf{X}_n = (d\mathbf{x}_{n-1} \cdots d\mathbf{x}_{n-s});$

end for

end while

Vector operations per MATVEC

Method	DOT	AXPY	Memory Requirements
IDR(1)	2	4	8
IDR(2)	$2\frac{2}{3}$	$5\frac{5}{6}$	11
IDR(4)	$4\frac{2}{5}$	$9\frac{7}{10}$	17
IDR(6)	$6\frac{2}{7}$	$13\frac{9}{14}$	23
Full GMRES	$\frac{n+1}{2}$	$\frac{n+1}{2}$	$n + 2$
BiCGSTAB	2	3	7

Relation with other methods

Although the approach is different, $IDR(s)$ is closely related to some Bi-CGSTAB methods:

- $IDR(1)$ and Bi-CGSTAB yield the same residuals at the even steps.
- $ML(k)BiCGSTAB$ (Yeung and Chen, 1999) seems closely related to $IDR(s)$, BUT
 - $IDR(s)$ is MUCH simpler (both conceptually and its implementation)
 - Other, more natural extensions are possible, e.g. to avoid breakdown.

Performance of IDR(s)

The IDR theorem states that

- it is possible to generate a sequence of nested subspace \mathcal{G}_j of shrinking dimension,
- but does not say how fast the dimension shrinks

It can be proven that the dimension reduction is (normally) s ,

So $\dim(\mathcal{G}_{j+1}) = \dim(\mathcal{G}_j) - s$.

IDR(s) requires at at most $N + \frac{N}{s}$ matrix-vector multiplications to compute the exact solution.

Numerical experiments

We will present two typical numerical examples

- A 2D Ocean Circulation Problem
- A 3D Helmholtz Problem

A 2D Ocean Circulation Problem

We compare IDR(s) with Full GMRES, restarted GMRES and Bi-CGSTAB.

This ocean example is representative for a wide class of CFD problems.

We will compare:

- Rate of convergence
- Stagnation level (of the true residual norm)

Stommel's model for ocean circulation

Balance between bottom friction, wind stress and Coriolis force.

$$-r \Delta \psi - \beta \frac{\partial \psi}{\partial x} = (\nabla \times \mathbf{F})_z$$

plus circulation condition around islands k

$$\oint_{\Gamma_k} r \frac{\partial \psi}{\partial n} ds = - \oint_{\Gamma_k} \mathbf{F} \cdot \mathbf{s} ds.$$

- ψ : streamfunction
- r : bottom friction parameter
- β : Coriolis parameter
- \mathbf{F} : Wind stress

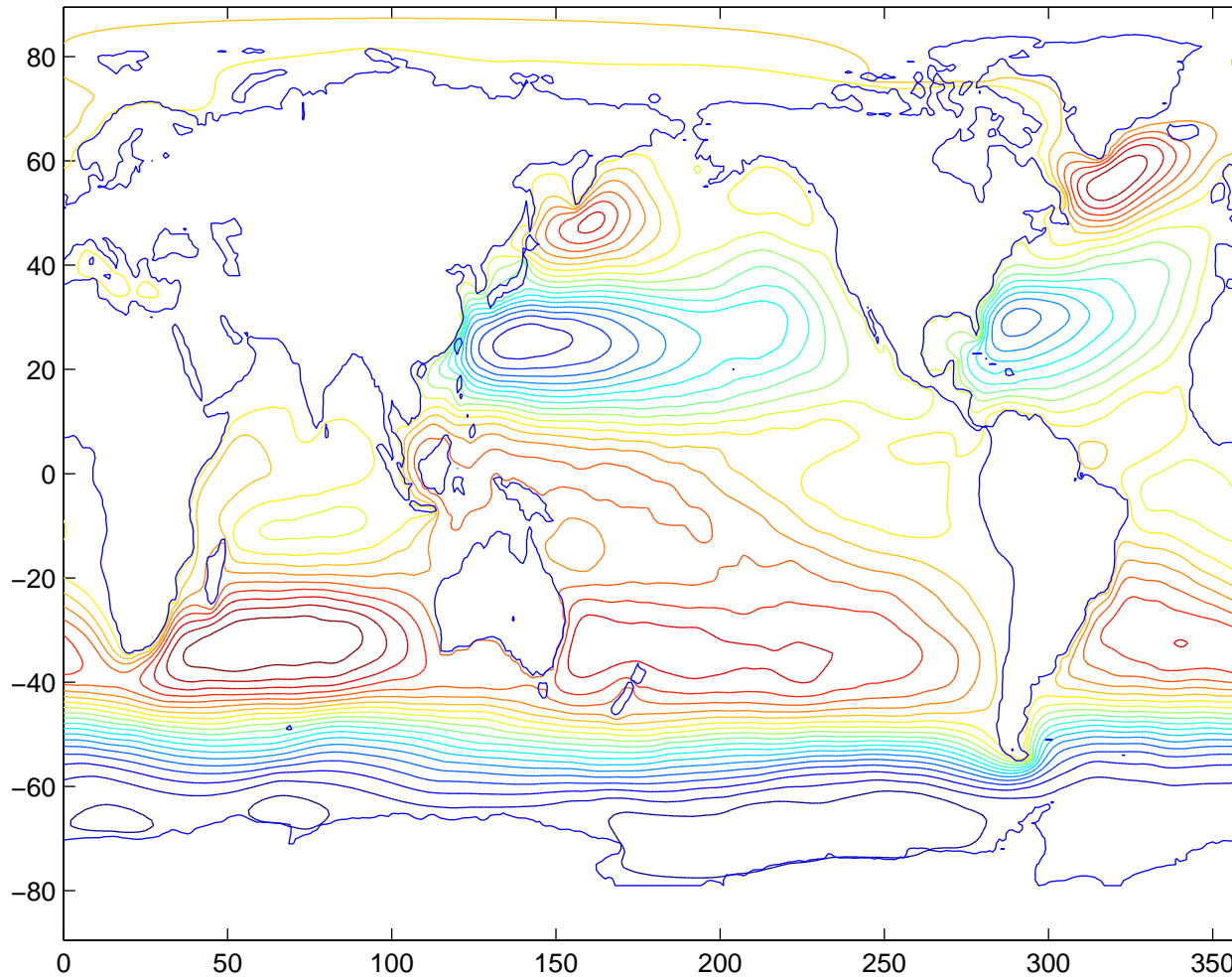
Discretization of the ocean problem

- Discretization with linear finite elements
- Results in nonsymmetric system of 42248
- Eigenvalues are (almost) real

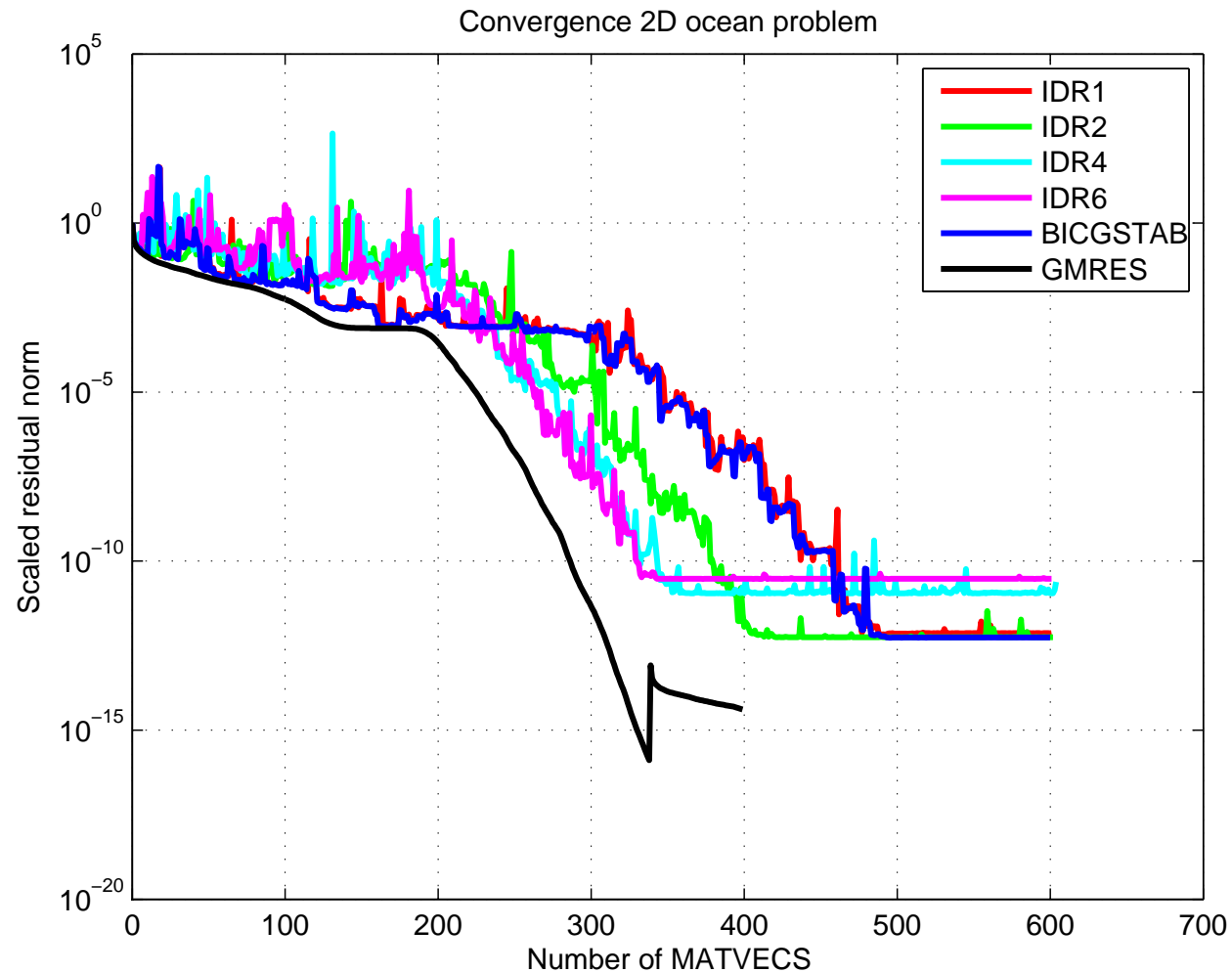
Solution parameters:

- ILU(0) preconditioning
- P : $s - 1$ random vectors plus r_0 (for comparison with Bi-CGSTAB)

Solution of the ocean problem



Convergence for the ocean problem



Some observations

- Required number of MATVECS decreases if s is increased. IDR(4) and IDR(6) are close to the optimal convergence curve of full GMRES.
- Convergence curves of IDR(1) and Bi-CGSTAB coincide.
- Stagnation levels of IDR(s) comparable with Bi-CGSTAB.

Required number of MATVECS

Method	Number of MATVECS	Vectors
Full GMRES	265	268
GMRES(20)	> 10000	23
GMRES(50)	4671	53
Bi-CGSTAB	411	7
IDR(1)	420	8
IDR(2)	339	11
IDR(4)	315	17
IDR(6)	307	23

Tolerance: $\|b - Ax_n\| < 10^{-8} \|b\|$

A 3D Helmholtz Problem

Example models sound propagation in a room of $4 \times 4 \times 4m^3$.

A harmonic sound source gives acoustic pressure field

$$p(\mathbf{x}, t) = \hat{p}(\mathbf{x})e^{2\pi ift}.$$

The pressure function \hat{p} can be determined from

$$\frac{-(2\pi f)^2}{c^2}\hat{p} - \Delta\hat{p} = \delta(\mathbf{x} - \mathbf{x}_s) \quad \text{in } \Omega.$$

in which

- c : the sound speed (340 m/s)
- $\delta(\mathbf{x} - \mathbf{x}_s)$: the harmonic point source, in the center of the room.

Boundary conditions

Five of the walls are reflecting, modeled by

$$\frac{\partial \hat{p}}{\partial n} = 0 ,$$

and the remaining wall is sound absorbing,

$$\frac{\partial \hat{p}}{\partial n} = -\frac{2\pi i f}{c} \hat{p} \text{ on } \Gamma_3.$$

Discretization

Discretization with FEM yields linear system

$$[-(2\pi f)^2 \mathbf{M} + 2\pi i f \mathbf{C} + \mathbf{K}] \mathbf{p} = \mathbf{b}$$

- Frequency $f = 100 \text{ Hz}$.
- System matrix complex, symmetric (but not Hermitian) and indefinite: **difficult for iterative methods**
- gridsize $h = 8 \text{ cm}$: 132651 equations

Solution parameters:

- ILU(0) preconditioning
- P : Initial residual plus $s - 1$ real random vectors
- Only comparison with BiCGstab(ℓ)

Results Helmholtz Problem

Method	Number of MATVECS	Elapsed time [s]
IDR(1)	1500	3322
IDR(2)	598	1329
IDR(4)	353	783
IDR(6)	310	698
BiCGstab(1)	1828	3712
BiCGstab(2)	1008	2045
BiCGstab(4)	656	1362
BiCGstab(8)	608	1337

Conclusions

- The IDR-theorem offers a new approach for the development of iterative solution algorithms
- The $\text{IDR}(s)$ algorithm presented here is quite promising and seems to outperform state-of-the-art Bi-CG-type methods for important classes of problems.

More information:

<http://ta.twi.tudelft.nl/nw/users/gijzen/software.html>

- Report: $\text{IDR}(s)$: a family of simple and fast algorithms for solving large nonsymmetric linear systems, submitted
- Matlab code, (includes preconditioning and deflation)