

Fast and Accurate Simulation of Close-to-Touching Discs in 2D Stokes Flow

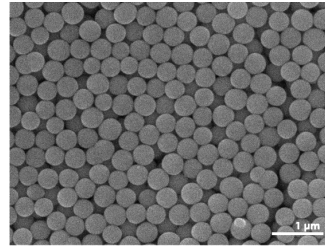
Dhairya Malhotra, Mariana Martinez Aguilar, Dan Fortunato



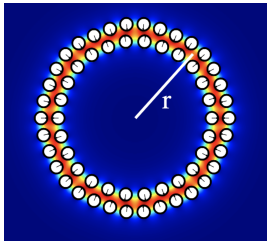
July 15, 2024

Applications:

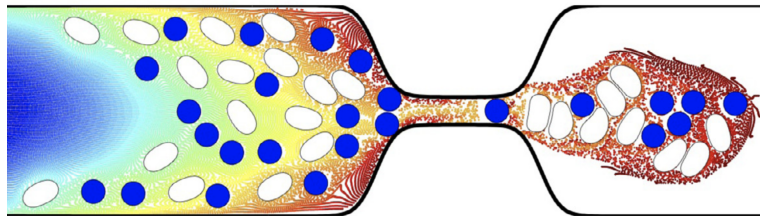
- Colloidal suspensions, emulsions
- Cellular biology, complex fluids
- Janus particles, clustering, self-assembly



Source: Wikipedia



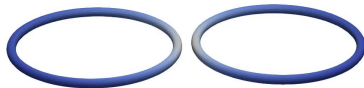
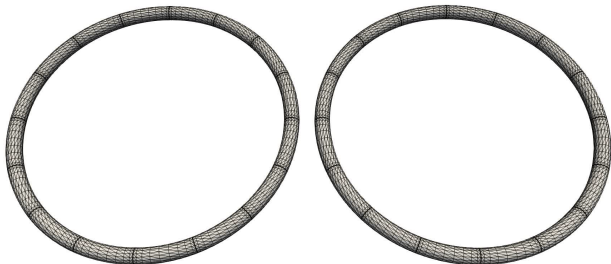
Fu, Quaipe, Ryham, Young (2021)



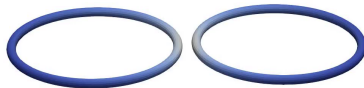
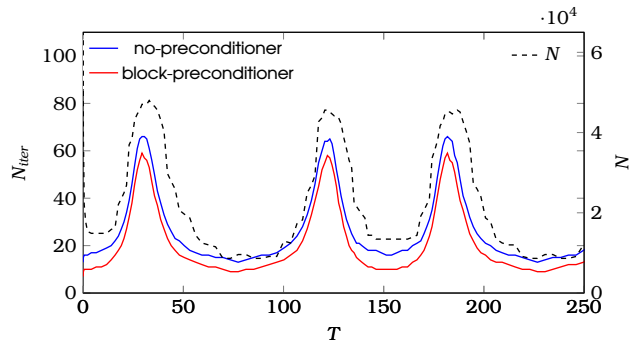
Lu, Rahimian, Zorin (JCP 2017)

Challenges

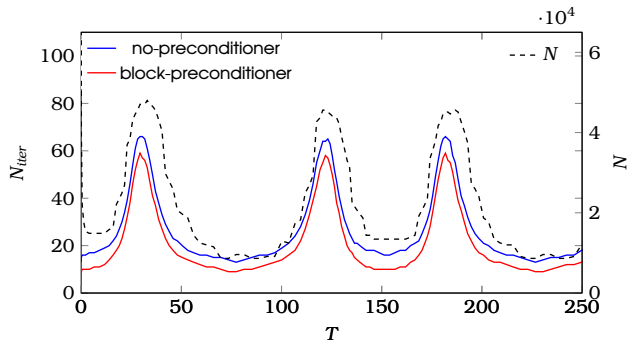
Example: Sedimenting rings in Stokes flow



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Close interactions:

$\sim 5\times$ more unknowns,

$\sim 5\times$ more GMRES iterations,

$\sim 5\times$ smaller ΔT

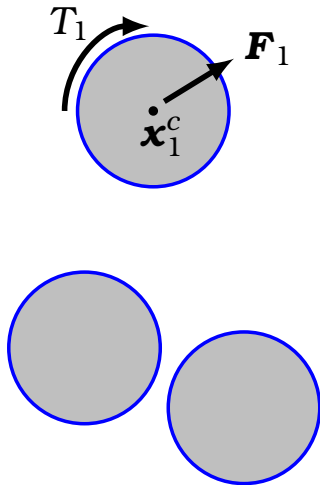
$> 100\times$ slower!

Problem Setup - Stokes Mobility

- n identical rigid discs $\Omega = \sum_{i=1}^n \Omega_i$
given radius R , centers $\mathbf{x}_i^c$, forces $\mathbf{F}_i$, torques T_i ,
velocity $\mathbf{V}(\mathbf{x}) = \mathbf{v}_i + \boldsymbol{\omega}_i \times (\mathbf{x} - \mathbf{x}_i^c)$.

- Stokesian fluid in $\mathbb{R}^3 \setminus \Omega$
$$\Delta \mathbf{u} - \nabla p = 0, \quad \nabla \cdot \mathbf{u} = 0,$$
$$\mathbf{u} \rightarrow 0 \text{ as } \mathbf{x} \rightarrow \infty.$$

- Boundary conditions on $\partial\Omega$,
$$\mathbf{u} = \mathbf{V} + \mathbf{u}_s.$$



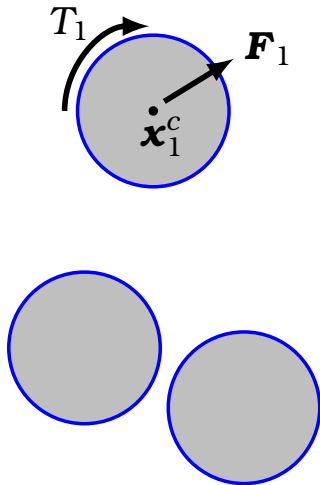
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- Boundary conditions on $\partial\Omega$,
$$\mathbf{u} = \mathbf{V} + \mathbf{u}_s.$$

unknown: $\mathbf{V}(\mathbf{u}_i, \boldsymbol{\omega}_i)$



Represent fluid velocity: $\mathbf{u}(\mathbf{x}) = \int_{\partial\Omega} S(\mathbf{x} - \mathbf{y}) \boldsymbol{\nu}(\mathbf{y}) + \int_{\partial\Omega} D(\mathbf{x} - \mathbf{y}) \boldsymbol{\sigma}(\mathbf{y})$

Boundary Integral Formulation

Represent fluid velocity: $\mathbf{u} = \mathcal{S}[\nu(\mathbf{F}_i, T_i)] + \mathcal{D}[\sigma]$

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and rigid body velocity: $\mathbf{V} = - \sum_{i=1}^{6n} \mathbf{v}_i \mathbf{v}_i^T \boldsymbol{\sigma}$

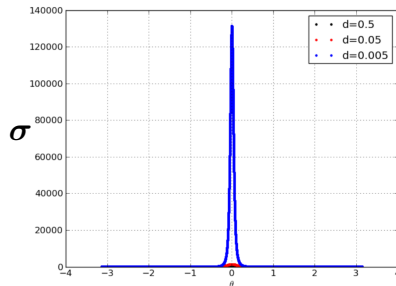
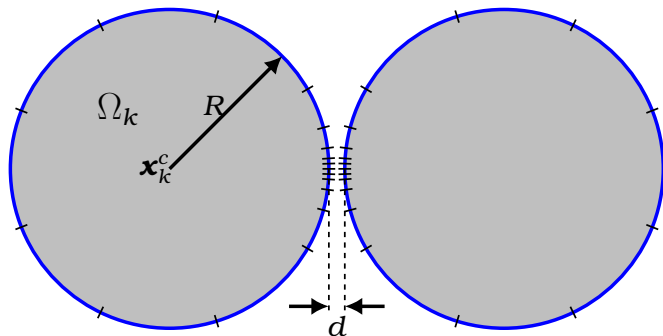
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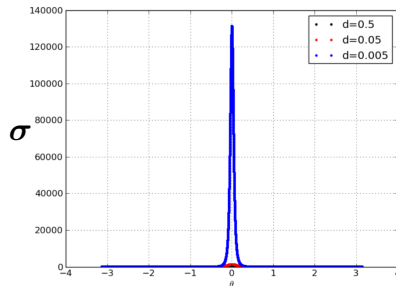
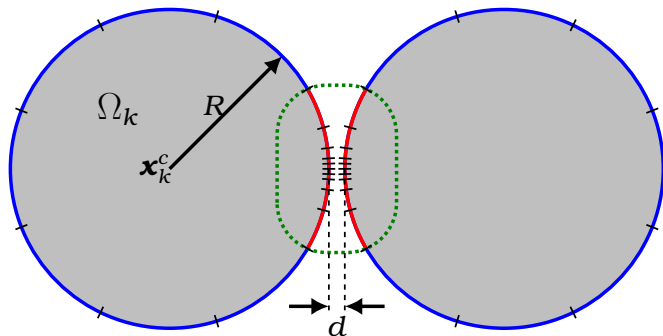
Applying boundary conditions ($\mathbf{u} = \mathbf{V} + \mathbf{u}_s$ on $\partial\Omega$),

$$(I/2 + D) \boldsymbol{\sigma} + \sum_{i=1}^{6n} \mathbf{v}_i \mathbf{v}_i^T \boldsymbol{\sigma} = \mathbf{u}_s - S \boldsymbol{\nu}$$

(Pozrikidis - Boundary Integral and Singularity Methods for Linearized Viscous Flow)



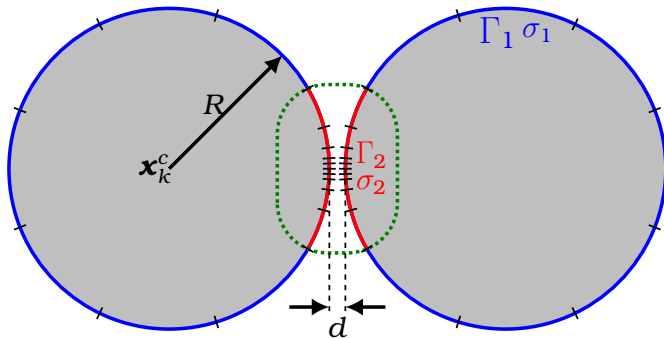
- Discretize $\partial\Omega$ into panels.
- Layer-potential operators:
 - adaptive quadrature for near integrals
 - special quadrature for singular integrals
- Solve BIE: $K\sigma = g$



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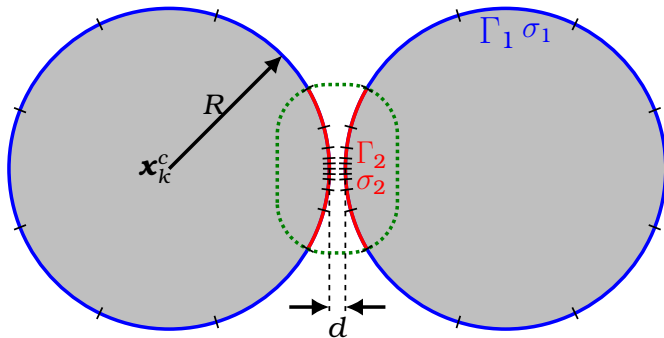
**Compress close-interactions,
and interpolate in d .**

Compressing Close Interactions



$$\begin{pmatrix} \mathcal{K}_{11} & \mathcal{K}_{12} \\ \mathcal{K}_{21} & \mathcal{K}_{22} \end{pmatrix} \begin{pmatrix} \sigma_1 \\ \sigma_2 \end{pmatrix} = \begin{pmatrix} g_1 \\ g_2 \end{pmatrix}$$

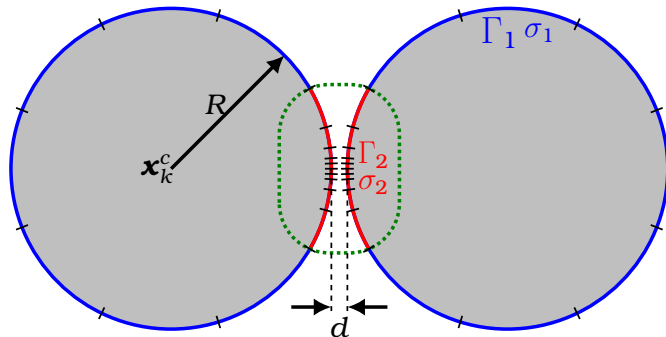
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Build compression using
RCIP method of Helsing

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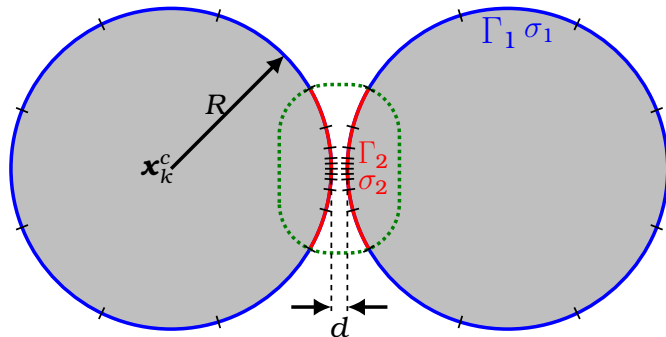
Build compression using
RCIP method of Helsing

Right precondition with $\mathcal{K}_{22}^{-1}$:

$$\begin{pmatrix} \mathcal{K}_{11} & \mathcal{K}_{12}\mathcal{K}_{22}^{-1} \\ \mathcal{K}_{21} & I \end{pmatrix} \begin{pmatrix} \sigma_1 \\ \bar{\sigma}_2 \end{pmatrix} = \begin{pmatrix} g_1 \\ g_2 \end{pmatrix}$$

where $\bar{\sigma}_2 = \mathcal{K}_{22}\sigma_2$

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$\implies$
coarsen

$$\begin{pmatrix} K_{11} & K_{12}^c R \\ K_{21}^c & I \end{pmatrix} \begin{pmatrix} \sigma_1 \\ \bar{\sigma}_2^c \end{pmatrix} = \begin{pmatrix} g_1 \\ g_2^c \end{pmatrix}$$

where $\bar{\sigma}_2 = \mathcal{K}_{22}\sigma_2$

where $R = W_c^{-1}P^T W_f K_{22}^{-1}P$.

Computing R_d On-the-Fly

Cost of computing R_d :

Direct: $\mathcal{O}((q \log d)^3)$

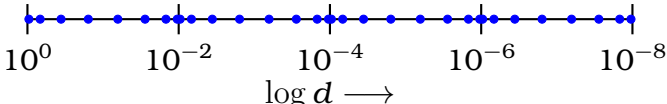
RCIP: $\mathcal{O}(q^3 \log d)$ [$\mathcal{O}(q^6 \log d)$ in 3D]

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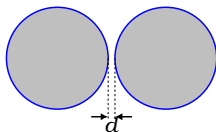
Interpolating R_d : Interpolated Compressed Inverse Preconditioning (ICIP)

$$R_{ij}(d) = \sum_{k=0}^{p-1} \alpha_k T_k(\log d)$$


$\log d \longrightarrow$

Interpolation cost: $\mathcal{O}(q^2 p)$ [$\mathcal{O}(q^4 p)$ in 3D]

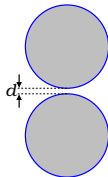
Errors (Stokes mobility with 2 discs):



d	Adaptive	Interpolating R_d			
	Discretization	$p = 8$	$p = 16$	$p = 24$	$p = 32$
1e-1	7.6e-15	1.0e-4	2.9e-07	2.1e-09	9.1e-12
1e-3	4.4e-13	3.4e-5	5.6e-10	4.8e-14	
1e-5	9.0e-09	1.5e-5	2.1e-12		
1e-7	4.3e-07	1.7e-5	4.1e-11		
1e-8	5.3e-08	6.3e-4	3.9e-09		

p : interpolation order

Iteration counts
for $\epsilon_{\text{GMRES}} = 1\text{e-}8$



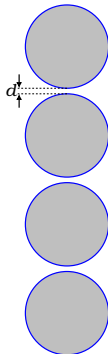
Adaptive discretization:

N_{disc}	$d = 1\text{e-}1$	$1\text{e-}2$	$1\text{e-}3$	$1\text{e-}4$	$1\text{e-}5$	$1\text{e-}6$	$1\text{e-}7$
2	15	37	104	337	1283	1848	2344

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2	18	20	21	21	21	21	21

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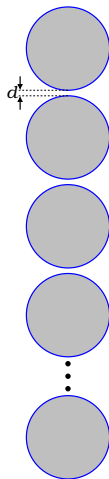
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2	15	37	104	337	1283	1848	2344
4	25	75	271	1134	3770	5301	6620

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2	18	20	21	21	21	21	21
4	28	34	36	37	37	37	37

Iteration counts
for $\epsilon_{\text{GMRES}}=1\text{e-}8$



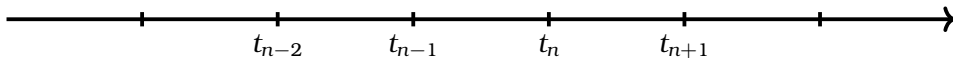
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16	35	147	629	2754	>8000		
64	36	148	683	3094			
256	37	149	683	3094			

Interpolated Compressed Inverse Preconditioning (ICIP):

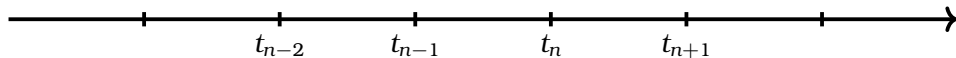
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2	18	20	21	21	21	21	21
4	28	34	36	37	37	37	37
16	46	71	74	80	86	87	88
64	49	96	108	131	186	237	251
256	49	98	110	134	220	371	608

Accelerating GMRES Solves



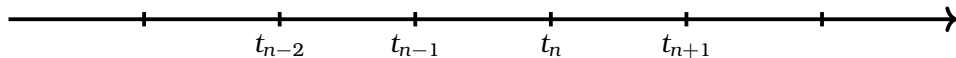
- Forward Euler: n -th time step
 - solve BIE using GMRES: $A_{y_n} \sigma_n = b_{y_n}$
 - advance to t_{n+1} : $y_{n+1} = y_n + h v(\sigma_n)$

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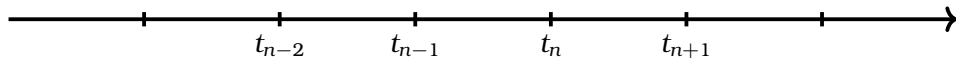


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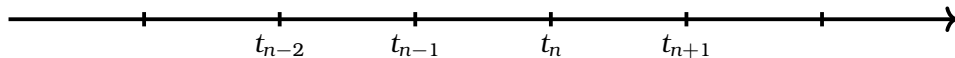
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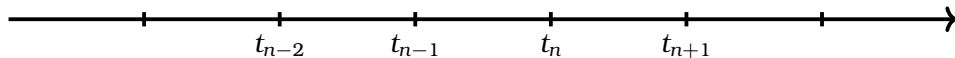
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- Re-use Krylov subspace from previous time step?
 - Krylov subspace: $X \leftarrow [b, Ab, \dots, A^{k-1}b]$
 - Compute QR decomposition: $QR \leftarrow AX$
 - Preconditioner: $P := I - QQ^T + XR^{-1}Q^T$

$$PAx = x \quad \text{for all } x \in \text{span}(X)$$

$$Py = y \quad \text{for all } y \perp \text{span}(X)$$

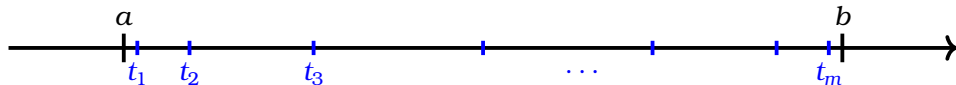


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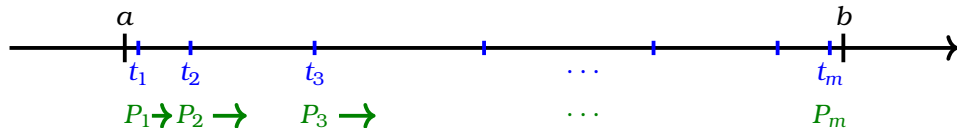
**Similar to
subspace deflation**

$$\begin{aligned} PAx &= x && \text{for all } x \in \text{span}(X) \\ Py &= y && \text{for all } y \perp \text{span}(X) \end{aligned}$$

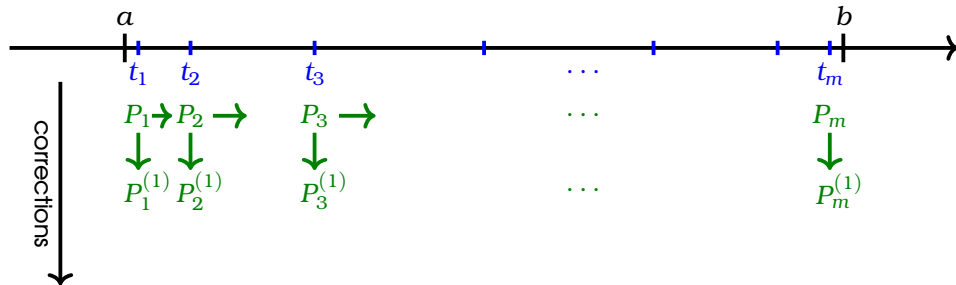
Krylov Preconditioning with SDC



Krylov Preconditioning with SDC



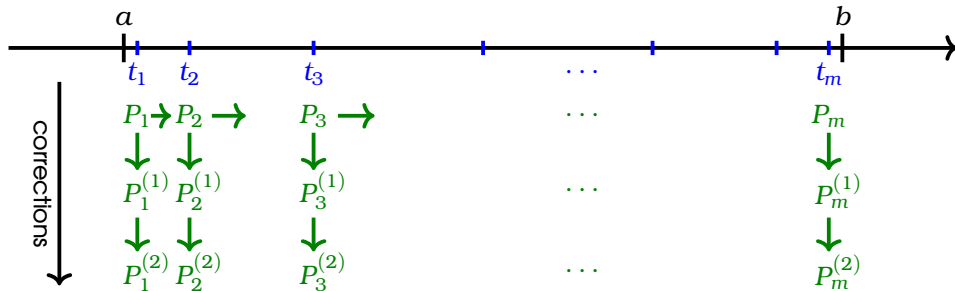
Krylov Preconditioning with SDC



Krylov Preconditioning with SDC



Krylov Preconditioning with SDC



GMRES iter without preconditioner:

correction $\rightarrow$	sub-step $\rightarrow$				
	66	66	66	66	66
	66	66	66	66	66
	66	66	66	66	66
	66	66	66	66	66

Krylov Preconditioning with SDC



GMRES iter without preconditioner:

correction $\rightarrow$	sub-step $\rightarrow$				
	66	66	66	66	66
	66	66	66	66	66
	66	66	66	66	66
	66	66	66	66	66

GMRES iter with preconditioner:

correction $\rightarrow$	sub-step $\rightarrow$				
	66	30	22	45	30
	35	17	33	28	24
	8	4	14	5	12
	1	1	2	2	4

Average iterations per GMRES solve: 30 (130 without Krylov preconditioner)



32 discs (36K unknowns), minimum distance: 1e-4, 10-th order SDC

7-digits accuracy in quadratures, GMRES solve, and time-stepping.

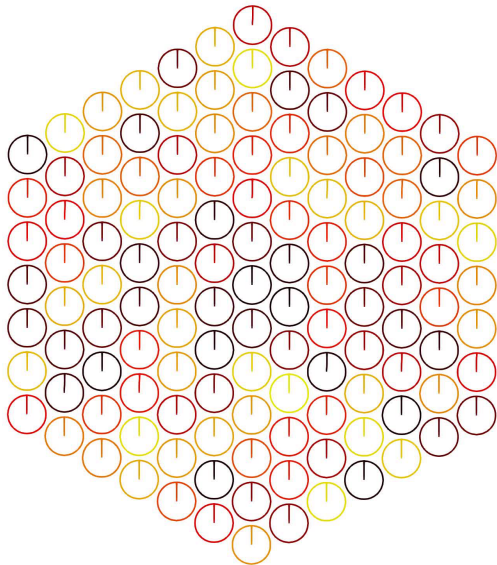
200K unknowns

127 discs.

Minimum distance: $1e-4$

10-th order adaptive SDC

5-digits accuracy in quadratures,
GMRES solve, and time-stepping.



- Interpolated Compressed Inverse Preconditioning (ICIP)
 - fast pairwise preconditioner using interpolation of precomputed compressed interaction operators.
- Krylov subspace preconditioner
 - precondition using Krylov subspace constructed during the previous time steps.
 - accelerate time-stepping, particularly Picard iterations in spectral deferred correction.

Ongoing work:

- Flows in confined geometries.
- Extension to spheres in 3D.

Limitations:

- Restricted to simple geometries (disks, flat planes)