

Augmented Lagrangian Preconditioner for Linear Stability Analysis of incompressible fluid flows on large configurations

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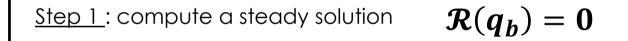


What is Linear Stability Analysis ?

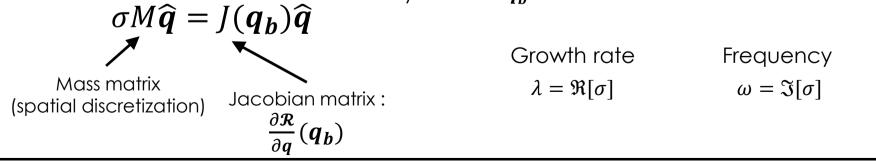
One wants to know if some steady solution of equation (1) is *temporally* stable or unstable :

$$\frac{\partial \boldsymbol{q}}{\partial t} = \boldsymbol{\mathcal{R}}(\boldsymbol{q}) \tag{1}$$

Method : Linear Stability Analysis

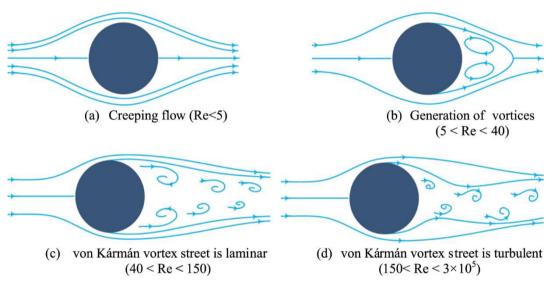


<u>Step 2</u>: test its stability for small monochromatic perturbations $\hat{q}(x)e^{\sigma t}$ around the steady solution q_b









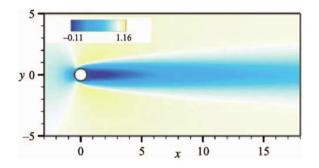
From [Goharzadeh & Molki, 2015]

Typical question : What is the critical Reynolds number above which the von Karman vortex street appears ?





<u>Step 1</u>: compute a steady solution

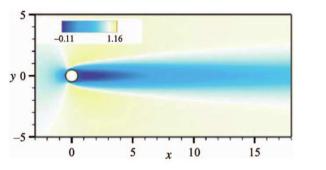


Steady Navier-Stokes solution (*Re* = 50) [Sipp et al, 2010]



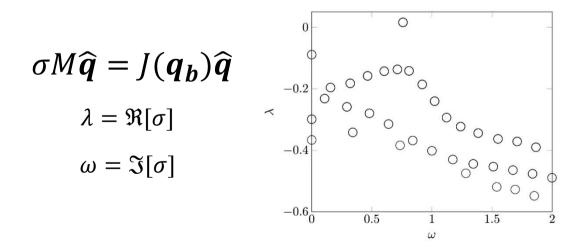


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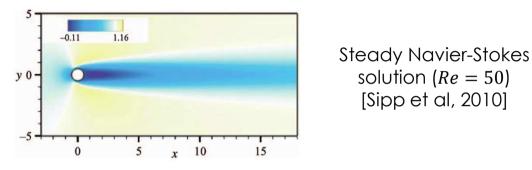
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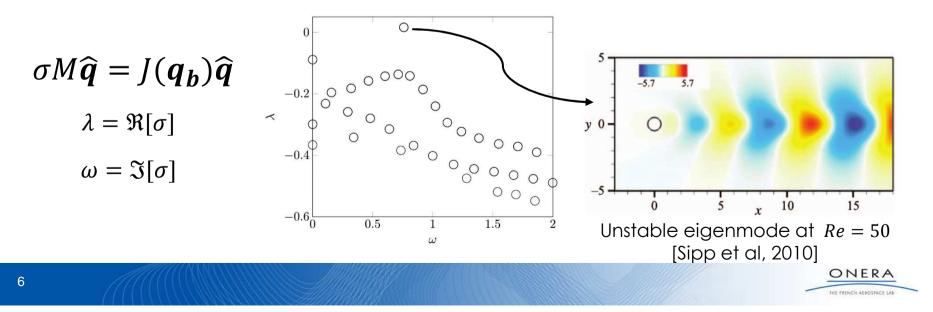




<u>Step 1</u>: compute a steady solution



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Why Linear Stability Analysis ?

<u>Some nice features :</u>

- Easy to determine a threshold value (sign of $\Re[\sigma]$)
- o Less expensive than nonlinear time-integration

But some computational burdens :

- Find a (not necessarily stable) steady solution : Newton method
 Multiple inversions of J
- Find internal eigenvalues of generalized EV problems : Krylov-Schur + shift-and-invert

> Multiple inversions of J - s M, where s is the shift





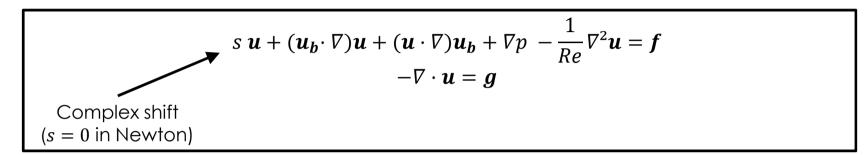
How to invert matrix of the type J - s M efficiently ?

- > For reasonably small configurations : direct sparse solvers (MUMPS, SUPERLU, etc)
- For large configurations : iterative method (GMRES, BiCGSTAB, ...) + good preconditioner



Introduction

Linearized incompressible Navier-Stokes operator (i.e. J - s M):



Once discretized with FE : classical **saddle-point** problem

$$\begin{pmatrix} A & B^T \\ B & 0 \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f \\ g \end{pmatrix}$$

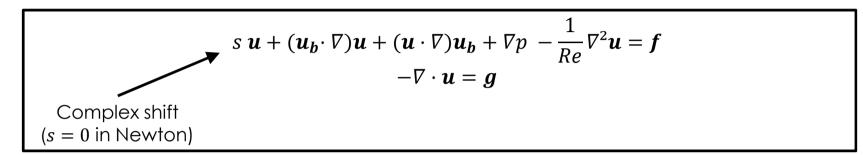
How to precondition this?

- o SIMPLE [Patankar 1980]
- o Stokes Preconditioner [Tuckerman, 1989] (based on adaptation of existing time-stepping code)
- o Pressure Convection Diffusion [Silvester et al. 2001]
- o Least-Squares Commutator [Elman et al. 2006]
- o Augmentated Lagrangian [Benzi and Olshanskii 2006], [Heister and Rapin 2013]



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- 1 Augmentation-based preconditioners
- 2 Performances
- 3 FreeFem++ parallel implementation
- 4 Parallel 3D numerical examples
- 5 Some further refinement ...



Augmented Lagrangian (algebraic augmentation)

$$\begin{pmatrix} A & B^T \\ B & 0 \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f \\ g \end{pmatrix} \longrightarrow \begin{pmatrix} A_{\gamma} & B^T \\ B & 0 \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f_{\gamma} \\ g \end{pmatrix} \qquad A_{\gamma} = A + \gamma B^T W^{-1} B$$
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Grad-Div augmentation (variational augmentation)

$$\int_{\Omega} s \, \boldsymbol{u} \cdot \boldsymbol{\check{u}} + (\boldsymbol{u} \cdot \nabla) \boldsymbol{u} \cdot \boldsymbol{\check{u}} + Re^{-1} \nabla \boldsymbol{u} : \nabla \boldsymbol{\check{u}} - p \nabla \cdot \boldsymbol{\check{u}}$$
$$+ \int_{\Omega} \gamma (\nabla \cdot \boldsymbol{u}) (\nabla \cdot \boldsymbol{\check{u}}) = \mathbf{0}$$
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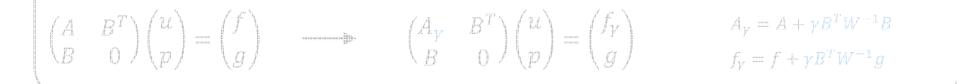
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Augmented Lagrangian leaves the discrete solution unchanged Grad-Div leaves the continuous solution unchanged



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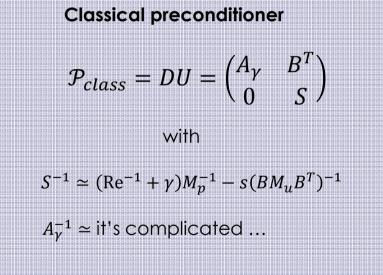
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1- Augmentation-based preconditioners

Classical vs. modified version

In both cases, the same block structure arises :

$$\begin{pmatrix} A_{\gamma} & B^T \\ B & 0 \end{pmatrix} = \begin{pmatrix} I & 0 \\ BA_{\gamma}^{-1} & I \end{pmatrix} \begin{pmatrix} A_{\gamma} & 0 \\ 0 & S \end{pmatrix} \begin{pmatrix} I & A_{\gamma}^{-1}B^T \\ 0 & I \end{pmatrix}$$
 $S = -BA_{\gamma}^{-1}B^T$ $S = -BA_{\gamma}^{-1}B^T$



Main features :

- > Mesh optimality
- Reynolds optimality
- > The higher γ , the less iterations (A_{γ}^{-1} ouch !)

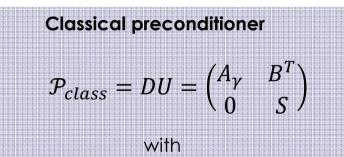


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$$S^{-1} \simeq (\text{Re}^{-1} + \gamma)M_p^{-1} - s(BM_uB^T)^{-1}$$

 $A_{\gamma}^{-1} \simeq \text{it's complicated} \dots$

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Modified preconditioner

$$\mathcal{P}_{modif} = \begin{pmatrix} \begin{bmatrix} A_{11,\gamma} & A_{12,\gamma} \\ 0 & A_{22,\gamma} \end{bmatrix} & B^T \\ 0 & S \end{pmatrix}$$
with

$$S^{-1} \simeq (\operatorname{Re}^{-1} + \gamma)M_p^{-1} - s(BM_uB^T)^{-1}$$

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2- Performances Choice of γ

The choice of a good γ is determinant for the preconditioning efficiency !

<u>Bright side</u>: since the preconditioner is independent of the mesh

Optimal γ can be found on a coarse mesh

<u>Dark side</u>: Optimal γ is problem and Re – dependent

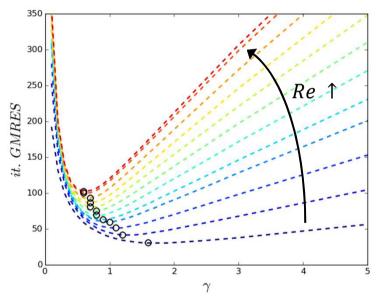


Figure : Influence of $Re \in [10,120]$ on optimal γ for modified Grad-Div preconditioner



CPU time in Newton method

	Volocity	ocity Pressure OFs DOFs	Full MUMPS			Modified Grad-Div		
Mesh			Facto (ms)	Reso (m s)	tot/ndof (µs)	Facto (ms)	Reso (ms)	tot/ndof (µs)
32x32	9900	1300	140	0	20	30	50	14
64x64	39000	5000	810	10	27	320	250	20
96x96	88000	11000	2250	40	33	840	580	21
256x256	623400	78200	34480	290	62	8090	4780	25

Averaged timings for 1 Newton iteration (**2D** lid-driven cavity, $Re = 100, \gamma = 0, 1$)



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8x8x8	9900	1300	3,2	0,01	263	0,6	0,26	112	
16x16x16	39000	5000	295	0,3	2675	21	2,8	274	

Averaged timings for 1 Newton iteration (**3D** lid-driven cavity, Re = 100, $\gamma = 0,1$)



CPU time for eigenvalue computation

	Velocity	Pressure	Full MU	MPS	Modified Grad-Div		
Mesh	DOFs	DOFs	Fact [s]	Eig [s]	Fact [s]	Eig [s] (it. inner GMRES)	
32x32	9890	1269	0,27	0,36	0,05	9 (29)	
64x64	39306	4978	1,7	1,3	0,45	34 (30)	
256x256	623482	78192	85	36	15	841 (30)	

Timings for computing 10 ev with ARPACK (**2D** lid-driven cavity, $Re = 100, \gamma = 0, 1$)



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16x16x16	107811	4913	753	31	57	353 (23)	

Timings for computing 10 ev with ARPACK (**3D** lid-driven cavity, $Re = 100, \gamma = 0, 1$)



Iterative strategy will be faster than the direct solver when : time facto >> time solving

- For Newton method : always the case because the jacobian is new at each iteration
- > For eigenvalue computation : true only for large configurations (3D typically)



Krylov subspace recycling techniques and eigenvalue computation

<u>Idea</u> : In Krylov-Schur + shift-invert, one has to perform many $(J - s M)^{-1}$ with the same matrix !

> Why not use Krylov subspace recycling from one linear solve to the next ?



2- Performances Krylov subspace recycling techniques and eigenvalue computation

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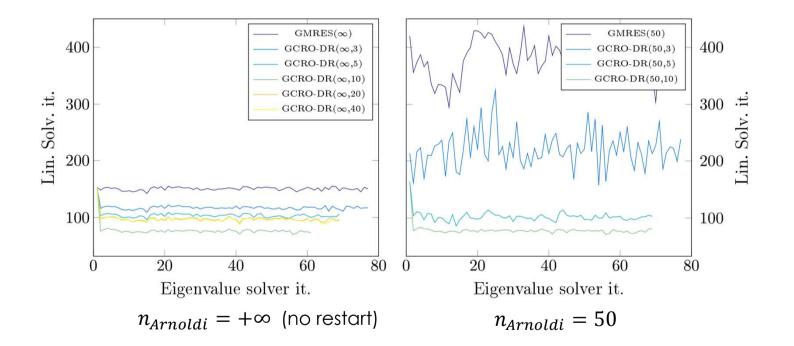


Figure : Effect of recycling during eigenvalue computation. Test case : 2D circular cylinder at Re = 50. Preconditioner : Modified Grad-Div with $\gamma = 1$ Eigenvalue solver : ARPACK with shift-invert

Ingredient 1: handle the preconditioner's block structure

PETSc solution : use of PCFIELDSPLIT preconditioner

<u>FreeFem++ interface</u> :



Ingredient 2: provide a specific Schur complement approximation

PETSc solution : PCFieldSplitGetSubKSP(pc, &nfields, &subksp)
KSPSetOperators(subksp[nfields-1], Sapprox, Sapprox)

<u>FreeFem++ interface :</u>

```
fespace Wh(th,[P2,P2,P2,P1]); // full space
fespace Qh(th,P1); // pressure space
Wh [u,v,w,p];
Wh [b, bv, bw, bp] = [1.0, 2.0, 3.0, 4.0];
string[int] names(4);
names[0] = "xvelocity" ;
names[1] = "yvelocity" ;
names[2] = "zvelocity" ;
names[3] = "pressure" ;
Oh pind;
pind[] = 1:pind[].n;
Wh [list, listv, listw, listp]= [0, 0, 0, pind]; // correspondance between Wh and Qh pressure DOFs
matrix[int] S(1);
S[0]=vSchur(Qh,Qh); // Schur complement approximation
// Set PETSc solver
set(A, sparams = " ... ... " ,
       fields = b[], names = names, schurPreconditioner = S, schurList = list[]);
```



<u>Ingredient 3</u> : provide the inverse Schur complement approx. as a composition of two simple inverses $S^{-1} \simeq (\text{Re}^{-1} + \gamma)M_p^{-1} - sL_p^{-1}$

 $S = (Re + \gamma)M_p - SL_p$

PETSc solution : use of PCCOMPOSITE preconditioner

```
FreeFem++ interface :
```



Ingredient 4 : Recycling of Krylov basis bewteen two consecutive solve $(J - s M)^{-1}$ in SLEPc

PETSc solution : interface HPDDM's solvers with PETSc/SLEPc

```
FreeFem++ interface :
```



Flow around low aspect-ratio flat plates [Marquet & Larsson 2015]

<u>Test case</u> :

- > 1 million tetrahedrons / Taylor-Hood FE pair / 4,8 millions DOFs
- \succ Re = 100

Solvers :

- Steady solution : Newton method with FGMRES preconditioned by **Modified Grad-Div** ($\gamma_{optimal} = 0,3$)
 - \blacktriangleright velocity sub-blocks solved with FGMRES preconditionned by ASM, overlap=1, tol=10⁻¹
 - Schur complement sub-block solved with CG preconditionned by jacobi, tol=10⁻³
- Eigenvalues : Krylov-Schur + shift-invert + GCRO-DR(100,30) preconditioned by **Modified Grad-Div** ($\gamma_{optimal} = 0,3$)
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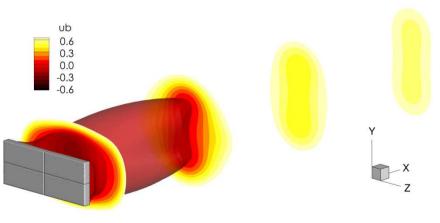
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Steady solution (axial velocity)



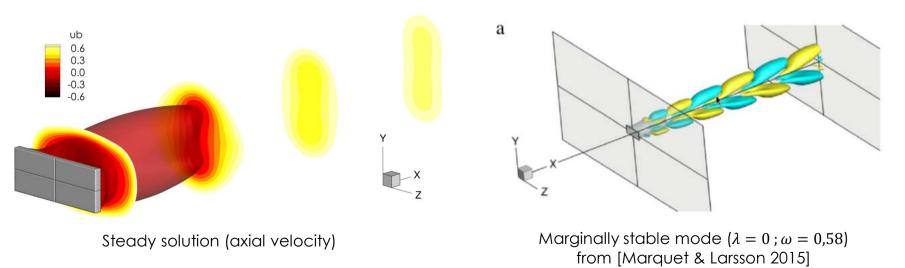
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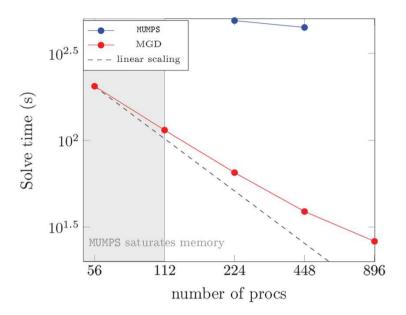
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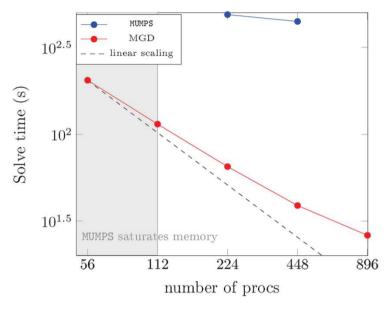
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Newton Method (average iteration time is represented)



4- Parallel 3D numerical examples Flow around low aspect-ratio flat plates [Marquet & Larsson 2015]

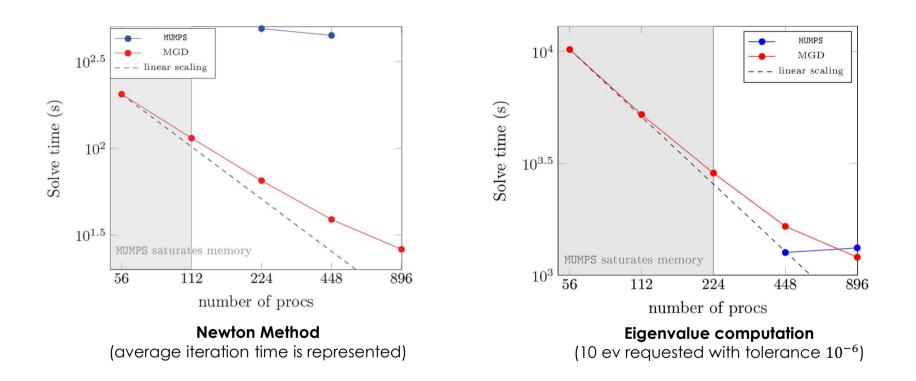


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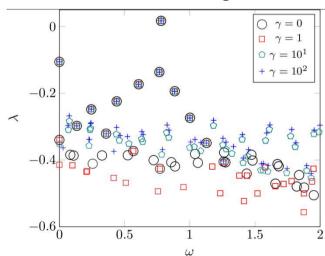
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Influence of γ on the solution ?

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$$- \int_{\Omega} (\boldsymbol{\nabla} \cdot \boldsymbol{u}) \boldsymbol{\check{q}} = \boldsymbol{0}$$

Grad-Div leaves the continuous solution unchanged



But ... changes the discrete solution !

Figure : Eigenvalue spectrum of the flow around a 2D circular cylinder at Re = 50

<u>Spatial discretization</u>: Taylor-Hood (P_2, P_1)



5- Some further refinement ...

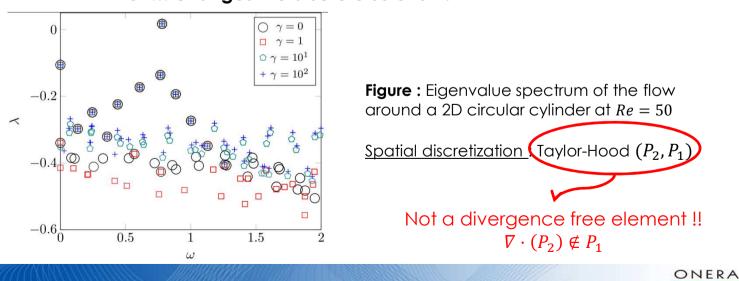
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Grad-Div augmentation (variational augmentation)

$$\int_{\Omega} s \boldsymbol{u} \cdot \boldsymbol{\check{u}} + (\boldsymbol{u} \cdot \boldsymbol{\nabla}) \boldsymbol{u} \cdot \boldsymbol{\check{u}} + Re^{-1} \boldsymbol{\nabla} \boldsymbol{u} : \boldsymbol{\nabla} \boldsymbol{\check{u}} - p \boldsymbol{\nabla} \cdot \boldsymbol{\check{u}}$$
$$+ \int_{\Omega} \gamma (\boldsymbol{\nabla} \cdot \boldsymbol{u}) (\boldsymbol{\nabla} \cdot \boldsymbol{\check{u}}) = \boldsymbol{0}$$
$$- \int_{\Omega} (\boldsymbol{\nabla} \cdot \boldsymbol{u}) \boldsymbol{\check{q}} = \boldsymbol{0}$$

Grad-Div leaves the continuous solution unchanged



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But ... changes the discrete solution !

5- Some further refinement ...

Influence of γ on the solution ?

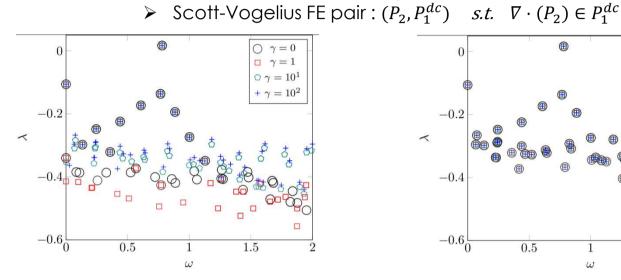


Figure : Eigenvalue spectrum of the flow around a 2D circular cylinder at Re = 50

<u>Spatial discretization</u>: Taylor-Hood (P_2, P_1)

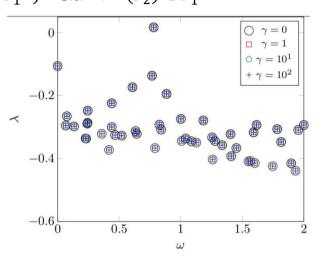


Figure : Eigenvalue spectrum of the flow around a 2D circular cylinder at Re = 50

Spatial discretization : Scott-Vogelius (P_2, P_1^{dc})

A few remarks :

- (P_2, P_1^{dc}) is inf-sup stable only on specific types of mesh (Hsieh-Clough-Toucher triangulation) 0
- We showed that when using divergence-free elements the variational and discrete augmentations are 0 equivalent

What if one uses a divergence-free element ?

It is unpreatical to use the discrete augmentation without divergence free elements due to the unsparse Ο nature of the augmentation term ...



Conclusion :

- Krylov subspaces iterative method preconditioned by Modified Grad-Div where shown to be efficient both for finding a steady solution and computing its spectrum
- Large 3D configurations and large number of processors accentuate the benefits of using the iterative strategy w.r.t. direct solver.
- **Ritz vector recycling** was shown to provide significant acceleration of the eigenvalue computation when using an iterative strategy for $(J s M)^{-1}$
- **A parallel implementation in FreeFem++**/PETSc/SLEPc was proposed.



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Perspectives :

- o Scalings must be improved : find an optimal preconditioner for velocity sub-blocks
- Extension for preconditioning turbulence models (RANS equations)
- o Towards coupled fluid-structure Linear Stability Analysis on large 3D configurations ...

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$$\begin{pmatrix} J_{ff} & J_{fs} \\ J_{sf} & J_{ss} \end{pmatrix}$$



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 Modified Grad-Div









Memory requirements in Newton method

Mesh	Velocity DOFs	Pressure DOFs	Memory direct MUMPS (Mb)	direct MUMPS Modified Grad-Div (Mb)	
16x16	2600	340	5	2x2	20
32x32	9900	1300	16	2x4	50
64x64	39000	5000	75	2x17	55
96x96	88000	11000	191	2x41	57
256x256	623400	78200	1862	2x353	62

Memory requirements (**2D** lid-driven cavity, Re = 100, $\gamma = 0,1$)

Mesh	Velocity DOFs	Pressure DOFs	Memory direct MUMPS (Mb)	Memory Modified Grad-Div (Mb)	Memory gain (%)
8x8x8	14700	729	143	3x21	56
16x16x16	107800	4900	2565	3x260	70

Memory requirements (**3D** lid-driven cavity, Re = 100, $\gamma = 0,1$)

