A fine-grained fully iterative ILU preconditioner for unsteady density variable Navier-Stokes equations

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Motivation

- 2 Fully iterative preconditioning strategy
- 3 Dual fluid flow simulation
- GPU implementation
- **5** Numerical experiments
- 6 Summary and conclusions

Algebraic problem

Let's focus on the solution of

 $A_n \mathbf{x}_n = \mathbf{b}_n, \quad n = 1, \dots$

where the matrices in the sequence A_n

- have order N;
- share the same (symmetric) sparsity pattern;
- slightly differ one from another;
- focus on ILU factorizations.

Goals:

- design a general purpose preconditioning strategy;
- exploit preconditioner from previous algorithmic steps;
- efficient execution on accelerators, in particular GPUs.



Incomplete LU factorization

Incomplete LU (ILU) factorization forms a robust class of preconditioners, however they involve **two sparse triangular linear systems** at each outer Krylov iteration. Drawbacks:

- ILU factorizations can generate significant fill-in;
- may be prone to instabilities.

Reordering techniques, such as the Reverse Cuthill-McKee (RCM) ordering, are been used to help alleviate this problem¹.

Focus:

- 1 Improve the efficiency of triangular solver on GPUs;
- ② Update LU factorization exploiting previous time steps to avoid computation from scratch.

¹Michele Benzi. "Preconditioning Techniques for Large Linear Systems: A Survey". In: *Journal of Computational Physics* 182 (2 2002).

Parallel exact triangular solver

Taking advantage of the **sparsity**, it is possible to group together independent rows by representing the dependencies as a directed graph². For example, a triangular system of size N = 8 can be solved in 2 algorithmic steps.





²Maxim Naumov. "Parallel Solution of Sparse Triangular Linear Systems in the Preconditioned Iterative Methods on the GPU". In: 2011.

Parallel exact triangular solver: RCM reordering

RCM may improve fill-in and stability, but it often erodes parallelism.



Approximate triangular solver³

Consider a sparse triangular linear system $T\mathbf{x} = \mathbf{b}$, D = diag(T) and D_B a block diagonal approximation of T. Jacobi(m):

$$\begin{cases} \mathbf{x}^{(k+1)} = D^{-1}\mathbf{b} + (I - D^{-1}T)\mathbf{x}^{(k)}, & k = 0, \dots, m-1 \\ \mathbf{x}^{(0)} = D^{-1}\mathbf{b}. \end{cases}$$
(1)

Block-Jacobi(*m*):

$$\begin{cases} \mathbf{x}^{(k+1)} = D_B^{-1} \mathbf{b} + (I - D_B^{-1} T) \mathbf{x}^{(k)}, & k = 0, \dots, m-1 \\ \mathbf{x}^{(0)} = D_B^{-1} \mathbf{b}. \end{cases}$$
(2)

³Edmond Chow et al. "Using Jacobi iterations and blocking for solving sparse triangular systems in incomplete factorization preconditioning". In: *Journal of Parallel and Distributed Computing* (2018). ISSN: 0743-7315.

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Consider a sequence of matrices A_n , n = 1, ..., with the same sparsity pattern S. The Iterative Thresholding Alternating LU^4 is an updating strategy.

$\mathsf{ITALU}(m)$

	Given $A_n \approx L_0 U_0$, compute $A_{n+1} \approx L U$	
1:	for $k = 0,, m - 1$ do	
2:	Compute $R_k = A_n - L_k U_k$	
3:	Compute $X_U = triu(L_k^{-1}R_k)$	Direct LU solver
4:	Apply dropping to X_U	
5:	$U_{k+1} = U_k + X_U$	▷ U update
6:	Compute $X_L = tril(R_k U_{k+1}^{-1})$	Direct LU solver
7:	Apply dropping to X_L	
8:	$L_{k+1} = L_k + X_l$	⊳ L update

⁴Caterina Calgaro, Jean-Paul Chehab, and Yousef Saad. "Incremental incomplete LU factorizations with applications". In: *Numerical Linear Algebra with Applications* 17 (5 2010).

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$\mathsf{ITALU}(m)$

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- 3:
- Apply dropping to X_{II} 4:
- $U_{k+1} = U_k + X_{II}$ 5:
- Compute $X_L = tril(R_k U_{k+1}^{-1})$ 6:
- 7: Apply dropping to X_{l}

$$L_{k+1} = L_k + X_L$$

Direct LU solver

▷ U update Direct LU solver

▶ L update

⁴Caterina Calgaro, Jean-Paul Chehab, and Yousef Saad. "Incremental incomplete LU factorizations with applications". In: Numerical Linear Algebra with Applications 17 (5 2010).

Theorem

Sequences $\{L_k\}$, $\{U_k\}$ converge respectively to the exact *L*, *U* factors, in no more then *N* steps.

However, the correction matrices are computed as the solution of

$$L_k X_U = R_k, \quad X_U = \operatorname{triu}(X_U), \\ U_k X_L = R_k, \quad X_L = \operatorname{tril}(X_L).$$
(3)

Inefficient on parallel machines, 2N sparse triangular systems at each iteration.

Fully iterative LU updates

Applying the Jacobi method

$$X_{L}^{(j)} = X_{L}^{(0)} + (I_{N} - D_{k}^{-1}L_{k})X_{L}^{(j-1)} \odot S, \quad X_{L}^{(0)} = (D_{k})^{-1} \operatorname{tril}(R_{k} \odot S),$$
(4)

where $D_k = \text{diag}(U_k)$, and, since $\text{diag}(U_k) = I_N$, we set

$$X_{U}^{(j)} = X_{U}^{(0)} + (I_{N} - U_{k})X_{U}^{(j-1)} \odot S, \quad X_{U}^{(0)} = \operatorname{triu}(R_{k} \odot S).$$
(5)

Dropping: component-wise product with $S = (s_{ij}), s_{ij} = 1$ if $(i, j) \in S$.

SITALU(m, j) (Scalable ITALU)

Given $A_n \approx L_0 U_0$, compute $A_{n+1} \approx LU$ 1: for k = 0, ..., m - 1 do

2: Compute
$$R_k = (A_n - L_k U_k)$$

3: Compute
$$X_L = X_L^{(j)}$$
 using (4)

$$4: \quad L_{k+1} = L_k + X_k$$

5: Compute
$$X_U = X_U^{(j)}$$
 using (5)

$$0: \quad U_{k+1} = U_k + X_k$$

Iterative LU solver
 L update
 Iterative LU solver
 U update

Navier-Stokes equations with variable density

Let $\Omega \subset \mathbb{R}^2$, the density dependent Navier-Stokes system on $(0, T] \times \Omega$ is

$$\partial_t \rho + \nabla \cdot (\rho \mathbf{u}) = 0, \tag{6}$$
$$\partial_t (\rho \mathbf{u}) + \nabla \cdot (\rho \mathbf{u} \otimes \mathbf{u}) - \mu \Delta \mathbf{u} + \nabla p = \rho \mathbf{f}, \tag{7}$$
$$\nabla \cdot \mathbf{u} = 0, \tag{8}$$

where the unknowns are

- u = u(t, x) is the velocity vector field,
- $p = p(t, \mathbf{x})$ is the pressure field,
- $\rho = \rho(t, \mathbf{x})$ is the density field.

Rayleigh-Taylor instability⁵

A heavy fluid fluid (density $\rho_{\rm max},$ in yellow) is superposed to a light fluid (density $\rho_{\rm min},$ in blue) under the action of a gravitational field.

The numerical difficulty essentially depends on:

- the Reynolds number Re;
- the Atwood number

$$At = rac{
ho_{\max} -
ho_{\min}}{
ho_{\max} +
ho_{\min}}.$$

⁵M. Dessole and F. Marcuzzi. "Fully iterative ILU preconditioning of the unsteady Navier–Stokes equations for GPGPU". In: *Computers & Mathematics with Applications* 77.4 (2019), pp. 907–927.

The numerical scheme

Use Strang time splitting⁶ and solve with a second order hybrid FE-FV scheme⁷:

• \mathbb{P}^1 Finite Volume approximation of the transport equation

 $\partial_t \rho + \nabla \cdot (\rho \mathbf{u}) = \mathbf{0}.$

• $\mathbb{P}^2 - \mathbb{P}^1$ Finite Element approximation of NS

 $\partial_t(\rho \mathbf{u}) + \nabla \cdot (\rho \mathbf{u} \otimes \mathbf{u}) - \mu \Delta \mathbf{u} + \nabla p = \rho \mathbf{f},$ $\nabla \cdot \mathbf{u} = 0.$

⁶Gilbert Strang. "On the Construction and Comparison of Difference Schemes". In: *SIAM Journal* on Numerical Analysis 5 (3 Sept. 1968).

⁷Caterina Calgaro, Emmanuel Creusè, and Thierry Goudon. "An hybrid finite volume–finite element method for variable density incompressible flows". In: *Journal of Computational Physics* 227 (9 2008).

NS: algebraic problem

Using a projection method, at each time step the linear problem is:

$$A_{n+1}U_i^{n+1} = F_{u_i}^{n+1}, \quad i = 1, 2,$$
(9)

$$L_{p}\Phi_{n+1} = F_{\Phi}^{n+1},$$
 (10)

$$M_{\rho}P_{n+1} = F_{\rho}^{n+1} \tag{11}$$

where L_p , M_p are the stiffness and mass \mathbb{P}^1 -matrices and

$$A_{n+1} = \frac{3}{2\Delta t} M_u(\rho^*) + \frac{1}{Re} L_u + NL(\bar{\mathbf{u}}^{n+1}, \rho^*).$$
(12)

where

- *M_u* is the mass matrix, depending on the current density fiend ρ^{*};
- L_u is the stiffness matrix
- NL is the nonlinear term matrix, evaluated on a second order extrapolation of the velocity field ūⁿ⁺¹ and the current density field ρ*.

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Fully iterative ILU for DVNS

Single node GPU-offloading



Experimental framework

The linear systems are solved with GMRES(30).

Abbr.	LU update	LU solver
ILU(0)	No	Direct exact solver
SITALU(<i>m</i> , <i>j</i>)	Yes	Direct exact solver
SITALU(m, j) + Jacobi(k)	Yes	Jacobi solver
SITALU(m, j)+block-Jacobi(k)	Yes	block-Jacobi solver

On what follows j = 1. Initialization is performed with ILU(0)⁸. Comparison metrics:

- the number of iterations for convergence (maxit= 3000);
- runtime of the solve phase (preconditioner computation/updating+GMRES).

Hardware: gpu01, NVidia GeForce GTX1060 GPU with 2560 CUDA cores.

⁸E. Chow and A. Patel. "Fine-Grained Parallel Incomplete LU Factorization". In: *SIAM Journal on Scientific Computing* 37.2 (2015), pp. C169–C193.

A closer look to block-Jacobi

Fine-grained block approximation:







(a) Lexicographic ordering.

(b) RCM ordering.

(c) Diagonal blocks, close up.

Trade-off: better parallelism, less efficiency.

Interplay between Reynolds and Atwood numbers

Rayleigh-Taylor instability is investigated in different settings, i.e. different values of the Reynolds number *Re* and the Atwood number *At*.

- Low, moderate and high Reynolds values, i.e. $Re = 10^{-2}$, 1000, 20000.
- Moderate, high and very high Atwood values, i.e. At = 0.5, 0.9, 0.98. Recall that

$$At = \frac{\rho_{\max} - \rho_{\min}}{\rho_{\max} + \rho_{\min}}.$$

For simplicity, we indicate also the density ratio $\rho_{\rm max}/\rho_{\rm min}=$ 3, 19, 100.



Condition number

Finally, the SITALU(1) preconditioner performs as well as ILU(0), meaning that it achieves its optimal behaviour.



Figure: Condition number in function of the Reynolds number at different density ratio.

Density ratio 3 (At = 0.5), Re = 20000



Figure: Evolution of the interface in time, N = 88981

Density ratio 3 (At = 0.5), Re = 20000



Figure: N=88981

Density ratio 3 (At = 0.5), Re = 20000

Preconditioner		Avg. iter. number	Avg. sol. Time (s)
	2	17.0	1.1701
ILU(0)	3	17.0	1.1727
	4	17.1	1.1789
	2	17.1	0.3850
SITALU(1)	3	17.2	0.3890
	4	17.5	0.3952
SITALU(1)+Jacobi(3)	2	18.3	0.0770
	3	18.4	0.0769
	4	18.7	0.0776

Table: Average values, the preconditioner is reused for *k* iterations.

Density ratio 100 (At = 0.98), $Re = 10^{-2}$



Figure: Evolution of the interface in time, N = 29341

Density ratio 100 (At = 0.98), $Re = 10^{-2}$



Figure: *N* = 29341

Density ratio 100 (At = 0.98), $Re = 10^{-2}$

Preconditioner		Avg. iter. number	Avg. sol. Time (s)
	2	216.30	6.1322
ILU(0)	3	216.33	6.1339
	4	216.38	6.1344
	2	216.30	3.3840
SITALU(1)	3	216.33	3.3849
	4	216.38	3.3949
	2	239.64	0.6730
SITALU(1)+Jacobi(3)	3	239.65	0.6733
	4	239.40	0.6739

Table: Average values, the preconditioner is reused for *k* iterations.

Density ratio 19 (At = 0.9), Re = 1000



Figure: Evolution of the interface in time, N = 88981

Density ratio 19 (At = 0.9), Re = 1000



Figure: *N* = 88981

Conclusions

- A fully iterative ILU preconditioner performs 80% better on a GPU.
- SITALU algorithm turns out to **efficient and inexpensive**, 2 to 3 times faster then recomputing the preconditioner from scratch.
- Preconditioner reuse has no global benefit to the execution times, and sometimes it causes the preconditioner to fail.

Further directions:

- The **number of sweeps could be adjusted dynamically**: the number of Jacobi sweeps *m* could be tuned on the residual norm reduction.
- Generalization to other preconditioning techniques should be investigated.

Thank you for listening!

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