Sparse grids Particle-in-Cell scheme for noise reduction in beam simulations



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CURSE OF DIMENSIONALITY VS CURSE OF NOISE

• Grid based algorithms scale **badly** with dimension:

Run time complexity $\kappa \sim \frac{h^{-d}}{\Delta t}$

Standard 2nd order scheme in space and time: $\epsilon \sim \Delta t^2$, $\epsilon \sim h^2$: $\kappa \sim \epsilon^{-\frac{d+1}{2}}$ "Curse of dimensionality"

Particularly bad for beam dynamics described by the Vlasov equation $\frac{\partial f}{\partial t} + \mathbf{v} \cdot \nabla f + \frac{q}{m} (\mathbf{E} + \mathbf{v} \times \mathbf{B}) \cdot \nabla_{\mathbf{v}} f = 0$ with d = 6.

► Pure particle methods scale much better with dimension:

 $\kappa \sim rac{dN}{\Delta t}$ Note: Ideal scaling, through Fast Multipole Method

Penalty paid with particle methods: slow convergence of error with N: ε ~ N^{-1/2}
For 2nd order in time scheme κ ~ dε^{-5/2} "Curse of noise"

THE PIC APPROACH – THE WORST OF BOTH WORLDS?

► N_g : Total # of grid cells

$$\epsilon \sim \Delta t^2 \;, \quad \epsilon \sim h^2 \;, \quad \epsilon \sim \left(\frac{N_p}{N_g}\right)^{-1/2} \quad (\text{Standard PIC scheme})$$

• Let d_r be the number of spatial dimensions

$$N_g \sim h^{-d_{\mathbf{r}}} \Rightarrow \left(\frac{N_p}{N_g}\right)^{-\frac{1}{2}} \sim N_p^{-\frac{1}{2}} h^{-d_{\mathbf{r}}/2}$$

• Complexity: $\kappa \sim d \frac{p}{\Delta t} \sim d \epsilon^{\left(-\frac{5}{2} + d_{\mathbf{r}}/2\right)}$

IC
$\sim \epsilon^{-3}$
$\epsilon^{-7/2}$
$\sim \epsilon^{-4}$
_

IMPROVING PIC

Bottom line:

- ► Grid based solvers scale best for 1-D and 2-D problems
- ► Pure particle based solvers scale best for 2-D and 3-D problems
- PIC always scale worse because of
 - ► Slow-converging statistical error: "Curse of noise"
 - Exponential dependence of κ on dimension: "Curse of dimensionality" (Although dimension reduced from d to d_r)

BUT

- Many advantages of PIC
 - Relative ease of implementation
 - Easier boundary conditions than in grid based codes
 - Well-suited for massive parallelization
 - Existence of many well established, successful solvers

Can one improve PIC by reducing both the grid based error and the noise?

SPARSE GRIDS COMBINATION TECHNIQUE

 Exact formula for the error from bilinear interpolation with discretization sizes h_x and h_y:

 $\epsilon := u_n(x,y) - u_E(x,y) = C_1(h_x)h_x^2 + C_2(h_y)h_y^2 + C_3(h_x,h_y)h_x^2h_y^2$



$$u_n(x,y) = \sum_{i+j=n+1} u_{i,j}(x,y) - \sum_{i+j=n} u_{i,j}(x,y)$$

ERROR CANCELLATION IN THE COMBINATION TECHNIQUE



 $\epsilon = C_1(h_x)h_x^2 + C_1(h_n)h_n^2$ $+ C_2(h_y)h_y^2 + C_3(h_x, h_y)h_x^2h_y^2$ $\epsilon = \underline{C_2(h_y)}h_y^{2-0} + C_2(h_n)h_n^2 + C_1(h_x)h_x^2 + C_3(h_x, h_y)h_x^2h_y^2$

ERROR AND COMPLEXITY ANALYSIS

$$u_n(x,y) = \sum_{i+j=n+1} u_{i,j}(x,y) - \sum_{i+j=n} u_{i,j}(x,y)$$

• The only surviving terms are $O(h_n^2)$; there are 2n + 1 such terms:

$$\epsilon = O(nh_n^2) = O(h_n^2|\log h_n|)$$

For full grid, $\epsilon = O(h_n^2)$

► Solve on 2n + 1 grids, each with $O(h_n^{-1})$ grid points :

$$\kappa = O(h_n^{-1}|\log h_n|)$$

For full grid, $\kappa = O(h_n^{-2})$

• Sparse: $\kappa \sim \epsilon^{-1/2} |\log \epsilon|^2$ Full: $\kappa \sim \epsilon^{-1}$

BREAKING THE CURSE OF DIMENSIONALITY

Example: Bilinear interpolation of $\overline{\sin(2\pi x)}\cos(3\pi y)$ at 50 random points in $[-1, 1] \times [-1, 1]$



Same idea applicable in higher dimension
e.g in 3D: combination along a diagonal *plane*

Sparse: $\kappa \sim \epsilon^{-1/2} |\log \epsilon|^{2(d-1)}$ **Full:** $\kappa \sim \epsilon^{-d/2}$

Much weaker dependence on dimension

- Applicable to higher order schemes
- ► Schemes with adaptive refinement have been proposed
- Limitations
 - Requires structured mesh
 - ► Requires more smoothness of function to be represented / Alignment with grid → we will return to this

SPARSE GRIDS FOR PIC

- Clear that sparse grids can be benefitial for the field parts of the PIC scheme (solve and interpolation)
- ► What about particle part of PIC?
- Error of approximating true particle density *ρ* with approximate density *ρ* using hat functions

 $\rho(\mathbf{x}_k) - \varrho(\mathbf{x}_k) = C_1(h_x)h_x^2 + C_2(h_y)h_y^2 + C_3(h_x, h_y)h_x^2h_y^2 + \xi_k,$

with ξ_k r. v. with $E[\xi_k] = 0$ and $Var(\xi_k) \approx 4Q\rho(\mathbf{x}_k)/9 \cdot 1/(h_x h_y N_p)$

- ► Blue terms are sources of grid based error. Same form as interpolation formula ⇒ good for sparse grids
- Yellow term is source of statistical noise. Using the Schwarz equality, one can show that sparse grids have the same benefitial effect on statistical noise¹

¹L.F. Ricketson and A.J. Cerfon, *Plasma Phys. Control. Fusion* **59** 024002 (2017)

SPARSE GRIDS FOR PIC – INTUITIVE ADVANTAGES

- ► Statistical noise in PIC depends on the # of particles per cell
- ► Sparse grids have larger cells ⇒ Sparse PIC has more particles per cell than standard PIC for a given overall # of particles

 \Rightarrow Sparse PIC has less numerical noise than standard PIC, for a given overall # of particles

 \Rightarrow Sparse PIC has lower memory requirements than standard PIC, for a given target accuracy

- The grids at the extremes of the grid hierarchy are the only ones to resolve the DeBye length, and do so only in one direction
- Sparse grids require far less memory to store than their full-grid counterparts

 \Rightarrow An entire sparse spatial grid easily fits on a single compute node

 \Rightarrow Much less communication and load-balancing overhead

SPARSE GRIDS RESULTS 2D plasma oscillations

 $N_p \sim 10^9$

 $N_p \sim 10^7$, Sparse PIC

 $N_p \sim 10^7$







3D plasma oscillations



SPARSE GRIDS ACCURACY AND MEMORY USAGE



- Sparse grids often lead to a significant reduction in computational time
- Sparse grids always lead to a significant reduction in memory usage

CURRENT LIMITS OF SPARSE PIC Illustration with the diocotron instability



- Sparse PIC: 7.8×10^5 particles, 1024×1024 grid, 225 seconds
- ▶ **Regular PIC**: 2.6×10⁶ particles,256×256 grid, 246 seconds
- Details of billows smeared out in sparse PIC

POLAR COORDINATES FOR DIOCHOTRON INSTABILITY







<u>Idea</u>: use inexpensive, low dimensional continuum equations or inexpensive, high noise PIC simulation to construct optimized coordinate system for sparse grids PIC

OPTIMIZED COORDINATES FOR SPARSE GRIDS

SUMMARY – FUTURE WORK

- Sparse grids can significantly decrease the grid based error and the numerical noise in PIC simulations
- The noise reduction comes from the larger number of particles per cell in sparse PIC than in a standard PIC scheme
- For certain test problems, we demonstrated gains in terms of accuracy and major drops in memory requirements
 For other problems, sparse PIC did not perform better than standard PIC
- Sparse PIC is still in its infancy. We are exploring ways to make it perform consistently better than standard PIC:
 - Use higher order interpolation and higher order shape functions to reduce the grid-based error
 - Construct optimized coordinate systems which best align with solution structure
 - ► Combine sparse grids with adaptive mesh refinement
- Let us know if you would like to code a sparse PIC solver tailored for your needs!