

# Particle-in-Cell (PIC) Simulations of Plasmas

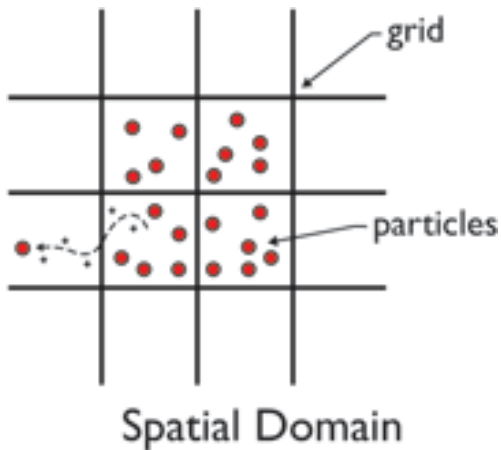
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Physics 761  
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# Cartoon PIC

Adapted from

[https://www.lanl.gov/science/NSS/issue2\\_2010/story4.shtml](https://www.lanl.gov/science/NSS/issue2_2010/story4.shtml)



**E** and **B** are known on the grid. Particles move freely.

# Why Doing Plasma Physics via Computer Simulations Using Particles Makes Good Physical Sense

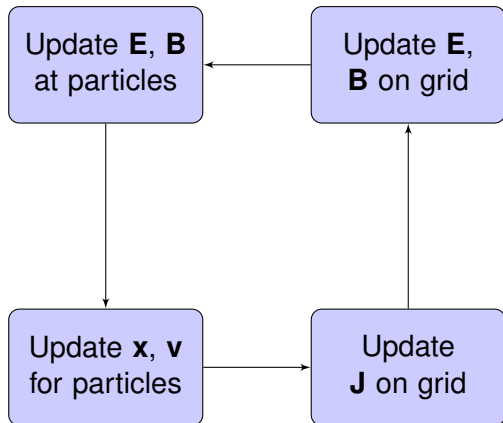
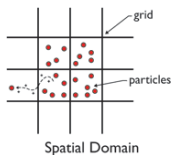
Inspired by Birdsall & Langdon, *Plasma Physics via Computer Simulation*

- ▶ Debye length  $\lambda_D = v_{th}/\omega_{pe} \ll L$ ; we care about  $\lambda \gtrsim \lambda_D$ .
- ▶ For a meaningful plasma  $N_D = n\lambda_D^3 \gg \gg 1$
- ▶ But that means

$$\frac{\text{KE (thermal kinetic energy)}}{\text{PE (electrostatic potential energy)}} = N_D^{2/3} \gg 1$$

- ▶  $\therefore$  *Particles interact collectively, not discretely.*
- ▶ Grids with  $\Delta x \lesssim \lambda_D$  capture the important physics without the unimportant inter-particle effects.

# Cartoon Timestep



## Updating $\mathbf{x}$ , $\mathbf{v}$ , $\mathbf{J}$ , $\mathbf{B}$ , and $\mathbf{E}$

- ▶ Field advancement:

$$\frac{\partial \mathbf{B}}{\partial t} = -c \nabla \times \mathbf{E} \quad \frac{\partial \mathbf{E}}{\partial t} = c \nabla \times \mathbf{B} - 4\pi \mathbf{J}$$

- ▶ Particle advancement:

$$\frac{d\mathbf{x}}{dt} = \mathbf{v} \quad \frac{d(\gamma \mathbf{v})}{dt} = \frac{q}{m} \left( \mathbf{E} + \frac{\mathbf{v}}{c} \times \mathbf{B} \right)$$

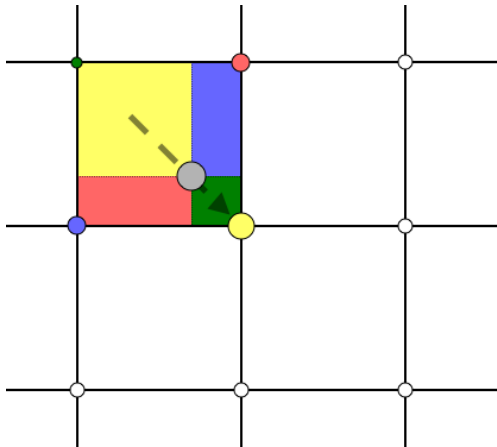
- ▶ Current density update:

$$\mathbf{J} = \sum_i q_i \mathbf{v}_i S(\mathbf{X} - \mathbf{x}_i)$$

where  $S(\mathbf{X} - \mathbf{x})$  is a shape function.

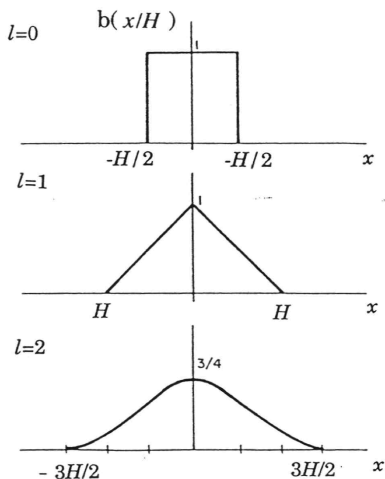
# Translating Between Particles and the Grid

Adapted from <https://www.particleincell.com/2010/es-pic-method/>



# Effective Particle Shapes (1D)

Adapted from <https://perswww.kuleuven.be/~u0052182/weather/pic.pdf>



► Nearest gridpoint

► First-order (cloud-in-cell)

► Quadratic spline

## Does PIC Satisfy $\nabla \cdot \mathbf{B} = 0$ and $\nabla \cdot \mathbf{E} = 4\pi\rho$ ?

Numerically,  $\nabla \cdot (\nabla \times) = 0$

$$\frac{\partial}{\partial t}(\nabla \cdot \mathbf{B}) = -c \nabla \cdot \nabla \times \mathbf{E} = 0$$

If  $\nabla \cdot \mathbf{B} = 0$  at  $t = 0$ , it remains so (ignoring round-off)

In contrast,

$$\frac{\partial}{\partial t}(\nabla \cdot \mathbf{E}) = c \nabla \cdot \nabla \times \mathbf{B} - 4\pi \nabla \cdot \mathbf{J} = -4\pi \nabla \cdot \mathbf{J}$$

To satisfy Gauss's Law requires

$$\frac{\partial \rho}{\partial t} + \nabla \cdot \mathbf{J} = 0$$



# Unfortunately . . .

Continuity is not, in general, satisfied

Corrections fall into two broad categories

- ▶ “Fix”  $\mathbf{E}$
- ▶ “Fix”  $\mathbf{J}$

An approach of the first type: Suppose a  $\Phi$  exists such that

$$\mathbf{E}' = \mathbf{E} - \nabla\Phi \quad \text{where} \quad \nabla \cdot \mathbf{E}' = 4\pi\rho$$

Find  $\Phi$  by solving

$$\nabla^2\Phi = \nabla \cdot \mathbf{E} - 4\pi\rho \equiv b$$

This ( $\nabla^2\Phi = b$ ) is Poisson's equation and can be solved many different ways: FFTs, matrix methods, multigrid methods, . . .

# An Alternative: Fluid vs. PIC Simulations

## Fluid (MHD)

Advantages:

- ▶ Correct on large scales
- ▶ Computationally fast

Disadvantages:

- ▶ Wrong at small scales

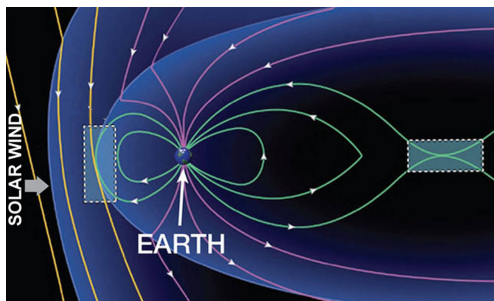
## Kinetic (PIC)

Advantages:

- ▶  $\approx$  All of the physics

Disadvantages:

- ▶ Must resolve important scales
- ▶ Computationally painful



# Resolution for Explicit PIC

For timestep  $\Delta t$ , grid spacing  $\Delta x$ , and velocity  $u$  a general constraint is

- ▶ CFL (Courant-Friedrichs-Lewy):

$$\frac{u\Delta t}{\Delta x} \leq 1$$

For plasmas also need to resolve important physical scales

- ▶  $\Delta x < (\lambda_D, \omega_{pe}, \rho_{Le})$
- ▶  $\Delta t < (\omega_{pe}, \omega_{ce})$

**Not resolving generally leads to numerical instability.**

# Kinetic Scales

How painful?

- ▶ Solar corona:  $B = 50 \text{ G}$ ,  $n = 10^9 \text{ cm}^{-3}$ ,  $L \approx 10^9 \text{ m}$ ,  
 $\tau \approx 10^3 \text{ s}$ 
  - ▶  $d_p \approx 10 \text{ m}$
  - ▶  $\Omega_{pc}^{-1} \approx 2 \times 10^{-6} \text{ s}$
  - ▶  $\omega_{pi}^{-1} \approx 2 \times 10^{-8} \text{ s}$
- ▶ Magnetosphere:  $B = 2 \times 10^{-4} \text{ G}$ ,  $n = 20 \text{ cm}^{-3}$ ,  
 $L \approx 10^4 \text{ km}$ ,  $\tau \approx 10^3 \text{ s}$ 
  - ▶  $d_p \approx 50 \text{ km}$
  - ▶  $\Omega_{pc}^{-1} \approx 0.5 \text{ s}$
  - ▶  $\omega_{pi}^{-1} \approx 2 \times 10^{-4} \text{ s}$
- ▶ Tokamak:  $B = 3 \times 10^4 \text{ G}$ ,  $n = 2 \times 10^{13} \text{ cm}^{-3}$ ,  $L \approx 10^2 \text{ cm}$ ,  
 $\tau \approx 10^{-2} \text{ s}$ 
  - ▶  $d_p \approx 5 \text{ cm}$
  - ▶  $\Omega_{pc}^{-1} \approx 3 \times 10^{-9} \text{ s}$
  - ▶  $\omega_{pi}^{-1} \approx 2 \times 10^{-10} \text{ s}$

# The Annoyances of Reality

## And How to Get Around Them

Besides real systems being much larger than kinetic scales, nature insists on making the situation worse.

- ▶  $m_p/m_e \approx 1836$
- ▶  $c/v_A \gg 1$

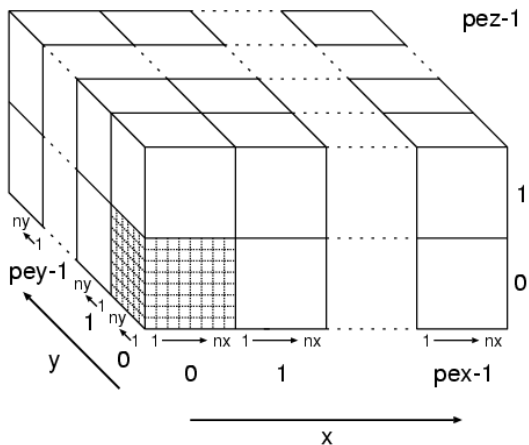
The resulting separation of scales is computationally challenging. To combat it, artificial values are often used

- ▶  $m_p/m_e = 400, 100, 25$
- ▶  $c/v_A = 20 - 50$

Potential unwanted side-effects (e.g.,  $v_{th,e} \rightarrow c$ ) must be kept in mind.

# PIC on Supercomputers

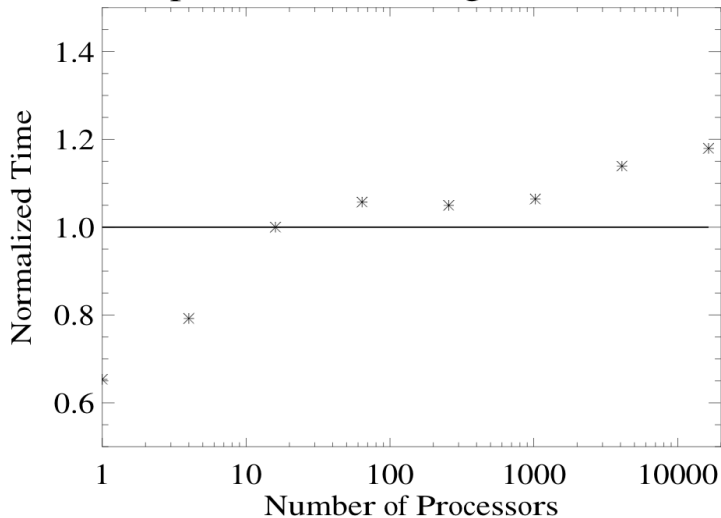
## Domain Decomposition



A useful simulation ( $\gtrsim 10^{10}$  particles) needs many cores working in parallel. Communication should be minimized.

# Supercomputer Performance

p3d: Weak Scaling on edison



# Brief Notes on PIC-Related Topics



# Accurate Numerical Differentiation

Not PIC-Specific

From the Taylor series

$$f(x_0 + \Delta x) = f(x) + \Delta x \left. \frac{df}{dx} \right|_{x_0} + \frac{(\Delta x)^2}{2} \left. \frac{d^2f}{dx^2} \right|_{x_0} + \mathcal{O}(\Delta x^3)$$

comes the approximation

$$\frac{df}{dx} = \frac{f(x + \Delta x) - f(x)}{\Delta x} + \mathcal{O}(\Delta x)$$

Incorporating a variation

$$f(x_0 - \Delta x) = f(x) - \Delta x \left. \frac{df}{dx} \right|_{x_0} + \frac{(\Delta x)^2}{2} \left. \frac{d^2f}{dx^2} \right|_{x_0} + \mathcal{O}(\Delta x^3)$$

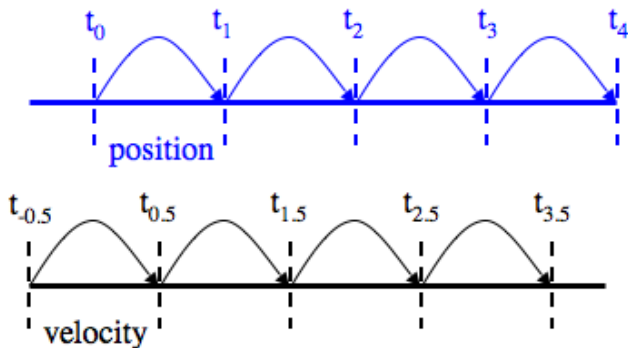
gives something more accurate

$$\frac{df}{dx} = \frac{f(x + \Delta x) - f(x - \Delta x)}{2\Delta x} + \mathcal{O}(\Delta x^2)$$

# Symmetry Reduces Errors and Helps Stability

From <https://www.particleincell.com/2011/velocity-integration/>

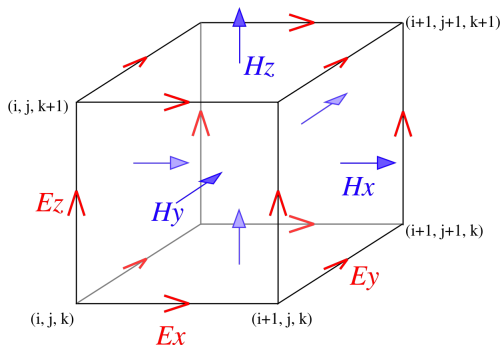
Basic leapfrog algorithm



# Gridding Systems

Adapted from <https://commons.wikimedia.org/wiki/File:Yee-cube.svg>

The Yee lattice is a popular – but not the only – choice.  
**E** is known on edges, **B/H** on faces.



The finite-difference versions of Maxwell's equations are nice,  
but bookkeeping is an annoyance.

# Explicit Versus Implicit Algorithms

Consider

$$\frac{\partial u}{\partial t} = D \frac{\partial^2 u}{\partial x^2}$$

Explicit discretization:

$$\frac{u_j^{n+1} - u_j^n}{\Delta t} = D \left[ \frac{u_{j+1}^n - 2u_j^n + u_{j-1}^n}{(\Delta x)^2} \right]$$

Implicit discretization:

$$\frac{u_j^{n+1} - u_j^n}{\Delta t} = D \left[ \frac{u_{j+1}^{n+1} - 2u_j^{n+1} + u_{j-1}^{n+1}}{(\Delta x)^2} \right]$$

Implicit is typically much more stable but requires much more work to solve.