CFD in Manufacturing and Medical Applications

Petros Koumoutsakos

Chair of Computational Science



www.cse-lab.ethz.ch

Modeling and Technology

 No aircraft is flown without having been designed with complex, mechanistic simulations



Modeling and Medicine

- Heuristics and Data
- Models ?



Dreamstime.com









M. H. MERKS, S. V. BRODSKY, M. S. GOLIGORKSY, S. A.NEWMAN, AND J. A. GLAZIER. CELL ELONGATION IS KEY TO IN SILICO REPLICATION OF IN VITRO VASCULOGENESIS AND SUBSEQUENT REMODELING. DEVELOPMENTAL BIOLOGY, 289(1): 44-54, 2006.

Crown Breakup - maragoni instability

drop impact onto an ethanol sheet

[2] S. T. THORODDSEN, T. G. ETOH, AND K. TAKEHARA. CROWN BREAKUP BY MARANGONI INSTABILITY. J. FLUID MECH., 557(-1):63-72, 2006.

Τα παντα ρει

16384 Cores - 10 Billion Particles - 60% efficiency

Runs at IBM Watson Center - BLue Gene/L





Chatelain P., Curioni A., Bergdorf M., Rossinelli D., Andreoni W., Koumoutsakos P., Billion Vortex Particle Direct Numerical Simulations of Aircraft Wakes, Computer Methods in Applied Mech. and Eng. 197/13-16, 1296-1304, 2008

Eidgenössische Technische Hochschule Züric

Tumor Induced Angiogenesis



CFD: Then and Now

$Re = 9500 \sim 10^6$ particles

1995 20 Days on CRAY YMP

2009 150sec on GPU

Rossinelli D., et.al., GPU accelerated simulations of bluff body flows using vortex particle methods, Journal of Computational Physics, 229, 9, 3316-3333, 2010

Outline

- COMPLEX DEFORMING GEOMETRIES
 - Meshing or Meshless ?
- FAST AND ACCURATE SIMULATIONS
 - Multiresolution and GPUs
- APPLICATIONS
 - Fish Hydrodynamics
 - Tumor induced Angiogenesis

PARTICLES: Lagrangian, Conservation and Other Laws

SPH, Vortex Methods

$$\rho_p \frac{D \mathbf{u_p}}{D t} = (\nabla \cdot \sigma)_p$$

 $\frac{d\mathbf{x}_{\mathbf{p}}}{dt} = \mathbf{u}_p$

$$m\frac{d\mathbf{u_p}}{dt} = F_p$$

MD, DPD, CGMD





PARTICLE APPROXIMATIONS

Function Mollification

$$\Phi_{\epsilon}(x) = \int \Phi(y) \zeta_{\epsilon}(x-y) \, dy$$

Smooth Particle Quadrature

$$\Phi^h_{\epsilon}(x,t) = \sum_{p=1}^{N_p} h^d_p \Phi_p(t) \zeta_{\epsilon}(x - x_p(t))$$



are Particles MESH Free ?

SURFACES -> **LEVEL SETS** $\Gamma(t) = \{ \mathbf{x} \in \Omega \mid \phi(\mathbf{x}, t) = 0 \}$

 $|\nabla \phi| = 1$

EVOLVING LEVEL SETS $\frac{\partial \Phi}{\partial t} + u \cdot \nabla \Phi = 0$

PARTICLES $\Phi_{\epsilon}^{h}(x,t) = \sum_{p=1}^{N_{p}} h_{p}^{d} \Phi_{p}(t) \zeta_{\epsilon}(x - x_{p}(t))$

Lagrangian Surface Transport

$$\frac{dx_p}{dt} = \mathbf{u_p}$$

$$\frac{D\Phi_p}{Dt} = 0$$





S. E. Hieber and P. Koumoutsakos. A Lagrangian particle level set method. **J. Computational Physics**, 210:342-367, 2005

Lagrangian vs Eulerian Descriptions



LAGRANGIAN DISTORTION

loss of overlap -> loss of convergence

Particles follow flow trajectories - Location distortion

EXAMPLE : Incompressible 2D Euler Equations

$$\omega = \nabla \times \mathbf{u} \quad \nabla \cdot \mathbf{u} = 0$$

 $\frac{D\omega}{Dt} = 0$

There is an exact axisymmetric solution



Are Particle Methods Grid Free ?

How to fix it?

- Modify the smoothing kernels (SPH Monaghan)
- Re-distribute particles with Voronoi Meshes (ALE Russo) EXPENSIVE UNSTABLE
- Re-initialise particle strengths (WRKPM Liu, Belytchko)

REMESHING : Re-project particles on a mesh

DOES NOT WORK

FXPFNSIVF

- NO MESH-FREE particle methods
- Can use all the "tricks" of mesh based methods
- High CFL
- Multiresolution & Multiscaling

Particle Remeshing



Koumoutsakos, J. Comp. Phys., 1997

Moment Conserving Interpolation : $Q_p^{\text{new}} = \sum_{p'} Q_{p'} M(jh - x_{p'})$

remeshed PARTICLE METHODS (rPM)

1.ADVECT : <u>Particles</u> ->Large CFL

2.REMESH : <u>Particles</u> to <u>Mesh</u> -> Gather/Scatter

3. SOLVE: Poisson/Derivatives on <u>Mesh</u>->FFTw/Ghosts

A:RESAMPLE: <u>Mesh</u> Nodes BECOME <u>Particles</u>

VORTEX RING COLLISION, Re = 1800



Experiments : P. Schatzle & D. Coles (1986)

VORTEX DYNAMICS at High Re



rPM : ADAPTIVE

yet inefficient !



Adaptive Mesh Refinement



- Support of unstructured gridsDifferent mesh orientations
- Low compression rate (Gradient, curvature)
- No explicit control on the compression error

Berger, Colella, J. Comp. Phys., 1989

Wavelet Compression



50:1

WAVELET PARTICLE METHOD

While particles are on grid locations

mollification kernel *basis/scaling function*

Multiresolution analysis (MRA) $\{\mathcal{V}^l\}_{l=0}^L$ of particle quantities

Refineable kernels as basis functions of \mathcal{V}^l

Wavelets as basis functions of the complements \mathcal{W}^l

$$\zeta_{k}^{l} = \sum_{j} h_{j,k}^{l} \zeta_{j}^{l+1}$$

$$= \sum_{j} \tilde{h}_{j,k}^{l} \zeta_{j}^{l} + \sum_{j} \tilde{g}_{j,k}^{l} \psi_{j}^{l}$$

$$= +$$

PARTICLETS : REMESHED PARTICLES + WAVELETS

wavelets



Wavelet Active Points = Active Grid Points

1.Remesh

2.Wavelets- Compress/Adapt

3.Convect

4. Wavelets Reconstruct

5.GOTO 1

M. Bergdorf, P. Koumoutsakos. A Lagrangian Particle-Wavelet Method, Multiscale Modeling and Simulation: A SIAM Interdisciplinary Journal, 5(3), 980-995, 2006



Wavelet-adapted grids



 $GHOSTS: \ easy \ to \ compute \ _\ (\ locally \) \ uniform \ filtering \ of \ the \ grid$

MULTIRESOLUTION LEVEL SETS

M. Bergdorf, P. Koumoutsakos. A Lagrangian Particle-Wavelet Method, Multiscale Modeling and Simulation: A SIAM Interdisciplinary Journal, 5(3), 980-995, 2006



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Shock Bubble Interaction

(M=3, At=0.8)

FINEST RESOLUTION EQUIVALENT 8000 x 8000 uniform grid ~40 times smaller adaptive

Hejazialhosseini B., Rossinelli D., Bergdorf M.,Koumoutsakos P., High order Finite Volume methods on Wavelet-adapted Grids with Local Time-Stepping on Multicore Architectures for the Simulation of Shock-Bubble Interactions, **J. of Comp. Physics**, 2010



0.2

: Air Jet

Block Grid for Multi/Many-core:



Neighbors look-up: less memory indirectionsLess #ghostsWithin a block: random access

Multiresolution + MultiCore + GPU

• MULTIPLE TASKS

1.task parallel,ghost computing -> multi-core
2.fine-grained data parallelism for RHS -> GPUs
3.Integration step -> multi-core

$$\mathbf{q^{new}} = \mathbf{q^{old}} + \delta t \mathbf{F} \left(\mathbf{q^{old}}, \nabla \mathbf{q^{old}} \right)$$
CUDA/OpenCL

- How much *faster* than CPU-only execution?
- **How much** *different* are CPU/GPU and CPU-only solutions?

Wavelet Blocks on GPUs



Multiple kernels for the GPU



Performance I : Strong Scaling

Strong scaling (effective 8000^2 - actual 40x less) vs. #GPUs, #CPU cores



Performance II : Time to Solution

Compared to a space adaptive, single-threaded solver:

- Algorithms : Local Time Stepping: **24X**
- Ghost Reconstruction : CPU optimization (vectorization): **1.8X**
- Ghost Reconstruction : Task-based parallelism (via TBB): 8X (over 12)
- GPUs as accelerators: **3X**

Overall Reduction in time to solution: ~ 1000

A comparison of CHOMBO vs MRAG

shock-bubble interaction



single-phase 2nd order PPM 56 min, 244 MB (+ 1 GPU: 7 min)

multi-phase 5th order WENO scheme

Rossinelli D., Hejazialhosseini B., Spampinato D., Koumoutsakos P., Multicore/Multi-GPU Accelerated Simulations of Multiphase Compressible Flows Using Wavelet Adapted Grids, SIAM J. Sci. Comput., 33, pp. 512-540, 2011

BOUNDARIES + ALGORITHMS



 $\rho \frac{D\mathbf{u}}{Dt} = \nabla \cdot \boldsymbol{\sigma} + f(\text{enforces b.c.})$



 $\rho \frac{D\mathbf{u}}{Dt} = \nabla \cdot \boldsymbol{\sigma} + f(\text{enforces b.c.})$

Penalization Method: $f(\mathbf{x}) = \lambda \chi_S (\mathbf{u}_S - \mathbf{u})$



 $\rho \frac{D\mathbf{u}}{Dt} = \nabla \cdot \boldsymbol{\sigma} + f(\text{enforces b.c.})$

Penalization Method: $f(\mathbf{x}) = \lambda \chi_S(\mathbf{u}_S - \mathbf{u})$ Immersed Boundary Method: $f(\mathbf{x}) = \kappa \delta_S(\mathbf{x}_S - \mathbf{x})$



Penalization Method: $f(\mathbf{x}) = \lambda \chi_S(\mathbf{u}_S - \mathbf{u})$ Immersed Boundary Method: $f(\mathbf{x}) = \kappa \delta_S(\mathbf{x}_S - \mathbf{x})$





SPHERE @ Re = 1000 with Effective Resolution 1024^3



TIMINGS : 4 days on 3 cores, 2.4 GHz - OpenN and MPI and TBB

Multi-body Simulations

TIMINGS : 3hours on 16 cores - TBB = SSE - Solver reaches 70% of the peak performence 180 GFlops over 210



Fish Schooling

Gazzola M., Chatelain P., van Rees W.M., Koumoutsakos P., Simulations of single and multiple swimmers with non-divergence free deforming geometries, **J. of Comput. Physics**, 2011



2 FISH (OBVIOUSLY)

Fast Swimmers Shape Optimization



Mean Shape During Evolution



How to escape fast?

Best Result of an Optimization for escape speed



COMPRESSIBLE FLOWS

Brinkman Penalization for Compressible Flow

Moving Boundaries



Shock – Ballut Interactions



Biological and medical simulations

J. Folkman: A key transition in the development of tumors is the recruitment of a vasculature

A Model of Sprouting Angiogenesis

Mechanism:

endothelial cells migrate towards source of growth factors

- form cords
- proliferate
- branch / fuse

Growth factor: VEGF

exists in two forms:solublebound to the matrix (bVEGF)

Release of bVEGF

endothelial cells secrete proteinases proteinases cleave bVEGF \rightarrow soluble



Multi-scale Modeling of Angiogenesis



[1] H. GERHARDT, M. GOLDING, M.FRUTTIGER, C. RUHRBERG, A. LUNDKVIST A. ABRAMSSON, M. JELTSCH C. MICHELL, .ALITALO, D. SHIMA AND C. BETSHOLTZ, VEGF GUIDES ANGIOGENIC SPROUTING UTILIZING ENDOTHELIAL TIP CELL FILOPODIA, J. CELL. BIOL, 2003

Modeling the Matrix

Fibers:

- straight
- random direction
- distribution of lengths

 $l = l_0 2^{m z}$ $\alpha \in \mathcal{U}([0, \pi])$ $z \in \mathcal{N}(0, 1)$

Indicator field : *e*

unity where fibers presentsmoothed (implicit filopodia)

Randomly oriented collagen fibril cartilage ECM imaged by TEM.

 α



Angiogenesis: in silico



Effect of Matrix structure on branching



FIBER LENGTH

statistics over n = 50 different matrices junctions identified with AngioQuant

Spatially Adaptive Stochastic Simulations of Gliomas

Time: 0.00 years

actual M = 10^7 effective M = 10^10

Bayati B., Chatelain P., Koumoutsakos P., Adaptive mesh refinement for stochastic reaction-diffusion processes, **J. of Comput. Physics**, 2011



Last Words

CHALLENGES

- Fast and/or Green Multi-scale Algorithms
- SIMULATIONS ARE DATA : UQ+P

APPLICATIONS

Biology, Nanotechnology and Fluids : Bridge Gaps and Disciplines

THANKS

• ETHZ + CSCS

Swiss National Science Foundation

• EU

• NVIDIA (ETHZ a CUDA Research Center)

