

Spatiotemporal Simulation of Biological Processes

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Studienmöglichkeiten @TUD-INF

- I) Nebenfach "Biowissenschaften"
- 2) M.Sc. "Computational Modeling and Simulation", Track "Computational Life Sciences"



Biology Computes

Cells execute **programs**:

- Genetic programs
- Communication programs
- Decision making
- Signaling networks
- Endosomal sorting

• . . .

Cells communicate by:

- chemical signals
- mechanical signals
- cell-cell contacts
- motion

• • • •





Meyerowitz, Caltech

Systems Biology

It's not about **using** computers to process biological data or to simulate biophysical models,

but

to understand the biological system itself as a **computing process**, reverse-engineer its "algorithms" and its "grammar", **and be able to reprogram (re-engineer) it.**

biological processes are inherently *algorithms* that nature has designed to solve computational problems.

algorithmsinnature.org

Computing in Biology

Computer science will be for 2020 biology what mathematics is for today's physics.

Microsoft Report "2020 Science"

Where and Why Computing in Biology?

Amount of data / Reproducibility

Complexity

Time/length scales

Ethics

Controllability

Observability















Variables measurable

Manual evaluation too slow or too unreliable

System behavior not apparent from description

Too big/small, slow/fast for experimental measurement

No living beings involved

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Computational Challenges in Biological Systems

- Hierarchical
- Regulated
- Complex shapes
- Non-equilibrium
- Nonlinear
- Coupled
- Plastic



Images: Wikipedia

Goad: Saysters Digntaomics

Source Code??





In order to understand the mechanistic working of biological systems, we also have to consider:

- Spatial organization and compartmentalization
- Temporal plasticity and dynamics
- Environmental influences
- Physics of interactions
- Regulatory mechanisms

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Scientific Computing for Systems Biology

A Typical Workflow in Systems Biology iss Federal Institute of Technology Zurich





What we want to do...



Particles: a Unifying Computational Framework

- Particle methods allow seamless treatment of continuous and discrete systems, both stochastically and deterministically
- In discrete systems, particles often correspond to real-world entities (atoms in molecular dynamics, cars in traffic simulations)
- In continuous systems, particles represent discretization points (fluid elements in flow simulations, mass in diffusion, etc.)



Examples:

Particles: a Unifying Computational Framework

Particles are computational elements, defined by their position and an arbitrary set of properties they carry.

discrete	continuous
 Particles = real-world objects Particle-particle interactions model physical (biological, financial, etc.) interactions Macroscale mathematical models are not required E.g.: molecular dynamics, agent-based models, Monte Carlo methods, etc. 	 Particles = Lagrangian tracer points Particle-particle interactions are designed such that the collective dynamics of the particles approximates a differential operator E.g.: Vortex Methods, SPH, PSE, etc.

Particle-particle interactions can be deterministic or stochastic



Deterministic particle methods for multiresolution spatiotemporal simulations

Particle-based bio-image processing

A parallel middleware and domain-specific language for particle-mesh methods on heterogeneous parallel computers

Talk Outline

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Continuum Particle Methods



Differential Operators over Particles

transport equation:

$$\frac{\partial f}{\partial t} + \nabla \cdot (f\mathbf{u}) = g$$

source term g often depends on derivatives of the field f, e.g.

$$g = \nabla \cdot (\nu \nabla f)$$

if f is diffused.

evolve particle strengths

$$\frac{\mathrm{d}\omega_p}{\mathrm{d}t} = v_p g$$

evaluation of derivatives of f is crucial

The PSE Operator Approximation



The Endoplasmic Reticulum (ER)



Figure: De Duve, Une visite guidée de la cellule vivante, 1987.





Figure: Purves et al., Life: The Science of Biology, W.H. Freeman.

The main **biosynthetic organelle** in Eukaryotes: Protein and lipid synthesis.

Enclosed by a contiguous membrane

FRAP: Fluorescence Recovery After Photobleaching

- Tag protein fluorescently
- Bleach region of interest with Laser
- Monitor influx of unbleached protein





Multi-Scale Issue in FRAP

- Discrepancy of scales: Observation of an integral quantity, averaged over Region Of Interest (ROI)
- ROI is larger than geometrical features of ER
- 2D projection or slice of the 3D object

Model needed to control the artifacts of the method and be able to correct for them!

A Computational Solution



Example Images

134

ss-GFP-KDEL VERO cells confocal microscope 3D PSF measured



Data: Helenius group, ETHZ

3D Deconvolving Segmentation



3D Reconstruction error

Reconstruction error

determined by:

- Threshold
- Resolution of the microscope

Find optimal threshold in the computer







Particle Method for Diffusion Simulations

Computational elements: Particles $(x_p, V_p, f_p), p = 1, ..., N$ at locations x_p with volumes V_p and property vector f_p :



$$\boldsymbol{f}_p = (u_p, \boldsymbol{x}_p, \ldots)$$

Diffusion:

Particles exchange MASS with their neighbors.

Degond & Mas-Gallic, Math. Comput. 53:509. 1989.

Diffusion in space

Formulation of the diffusion operator on particles

For (anisotropic) diffusion: $\frac{du_p}{dt} = \sum_{q \neq p} \sigma_{\epsilon}(\boldsymbol{x}_p, \boldsymbol{x}_q, \boldsymbol{D}, t)(u_q - u_p)V_q$ Degond & Mas-Gallic, Math. Comput. 53:509. 1989.

Extension to any differential operator:

$$L_h^{\beta} f(\boldsymbol{x}_p) \approx \frac{1}{\epsilon^{|\beta|}} \sum_q V_q \left(f(\boldsymbol{x}_q) \pm f(\boldsymbol{x}_p) \right) \eta_{\epsilon}^{\beta}(\boldsymbol{x}_p - \boldsymbol{x}_q)$$

Eldredge et al., J. Comp. Phys. 180:686. 2002.





Lumen



Sbalzarini et al., Biophys. J. 89(3):1482. 2005.

Simulation vs. Experiment



Beyond Experiments



FRAP simulations in the lumen of different ER

All simulation use the same diffusion constant

Influence (artifact) of geometry: **250%**

Sbalzarini et al., Biophys. J. 89(3):1482. 2005.

A new method for solving PDEs on surfaces





Membrane

Sbalzarini et al., Biophys. J. 90(3):1. 2006.





Deterministic particle methods for multiresolution spatiotemporal simulations

Particle-based bio-image processing

A parallel middleware and domain-specific language for particle-mesh methods on heterogeneous parallel computers

A Particle Method for Image Processing

- Model: The method is a approximates the gradient and hence optimizes any function.
- Deformable representation: Discrete, explicit representation with labels (colors) and particles:



• **Topological control** with *digital topology*

Cardinale, Paul, Sbalzarini, ITIP 2012.

Parallelization over Particles

3D 512x512x12

2D 240x180



Main source of speedup: use of texture memory!

Eyad Ebrahim, Master Student 2011.

Piecewise Smooth Image Model



3D Piecewise Smooth Segmentation

Splits/Handles decrease the energy and hence arise naturally during optimization.



Data: Zebra-fish germ cells. Mohammad Goudarzi, University of Münster

Cardinale, Paul, Sbalzarini, ITIP 2012.

Whole-Embryo Image Analysis





Data: Andy Oates, MPI-CBG

Cardinale, Paul, Sbalzarini, ITIP 2012.



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OpenFPM

Middleware implementation of particle-mesh abstractions.



Open Particle Mesh Environment (OpenPME)



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Main Innovation

Compile-time code generation



Parallel Particle-Mesh Abstractions

Sbalzarini et al., J. Comput. Phys. 215:556. (2006) I. F. Sbalzarini, Intl. J. Distr. Systems & Technol. 1 (2), 40 (2010)



Dynamic Load balancing



particles.decompose()
particles.redecompose()

CPU 0 CPU 1 CPU 2 CPU 3

File I/O

VTK: Visualization grid.write("my_file") particles.write("my_file")

HDF5: Save the full distributed data-structures

grid.save("my_file")

```
particles.load("my_file")
```



Lennard Jones Code Example

<pre>double sigma12; double sigma6; double r_cut2; constexpr int velocity_prop = 0; constexpr int force_prop = 1;</pre>	Constants	<pre>Particles definition typedef aggregate<point<3,double>,Point<3,double>> part_prop; vector_dist<3,double, part_prop > particles(0,box,bc,ghost);</point<3,double></pre>
		Initialization
<pre>for (size_t i = 0; i < 10000 {</pre>); i++)	Verlet-list velocity algorithm
<pre>velocity = velocity + 0.5 position = position + velocity</pre>	*dt*force; ocity*dt;	1. Calculate $\vec{v} \left(t + \frac{1}{2}\Delta t\right) = \vec{v}(t) + \frac{1}{2}\vec{a}(t)\Delta t$. 2. Calculate $\vec{x}(t + \Delta t) = \vec{x}(t) + \vec{v} \left(t + \frac{1}{2}\Delta t\right)\Delta t$.
<pre>particles.map(); particles.ghost_get<>();</pre>		
<pre>particles.updateCellList(I force = applyKernel_in_signal</pre>	NN); m(particles,NN	3. Derive $ec{a}(t+\Delta t)$ from the interaction potential using $ec{x}(t+\Delta t)$. , lennard_jones);
<pre>velocity = velocity + 0.5 }</pre>	*dt*force;	4. Calculate $ec{v}(t+\Delta t)=ec{v}\left(t+rac{1}{2}\Delta t ight)+rac{1}{2}ec{a}(t+\Delta t)\Delta t$.
<pre>Ghost<3,float> ghost(r_cut); ln_force lennard_jones;</pre>		}
		<pre>opentpm_tinalize(); }</pre>

Compact scalable simulations



Performance



LAMMPS* MD Lennard-Jones 216 thousand particles

*S. Plimpton, Fast Parallel Algorithms for Short-Range Molecular Dynamics, J Comp Phys, 117, 1-19 (1995)

^oCrespo et al, **DualSPHysics: open-source parallel CFD solver on Smoothed Particle Hydrodynamics (SPH).** Computer Physics Communications, 2015 ^oC. A. Rendleman, at al, **Parallelization of structured, hierarchical adaptive mesh refinement algorithms. Computing and Visualization in Science,**

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Multi-GPU automatically



(SPH) GTX: 1080 is 100 to 200 time faster (for float) than E5-2670, 1 core

The PPME Language for parallel computing

Performance

Simulation with 10⁵ particles. Turing patterns after 40,000 time steps.

Molecular Dynamics with PPML

126 PPML vs. 516 Fortran lines for the code

Brain electromagnetism

Solve the quasi-stationary Maxwell equations on particle distributions adapted to head/brain geometries from CT/MRI scans

Solve the forward problem for EEG/MEG source localization.

Biomechanics

Simulating the biomechanics of lipid membranes using particle phase field methods

Equilibrium shape of an Erythrocyte

Imagine...

Freie, offene Software!

Bildanalyse: MOSAICsuite for Fiji/ImageJ

- Segmentierung, Verbesserung, Tracking, Objektanalyse
- <u>mosaic.mpi-cbg.de</u>

Simulation: OpenFPM

- Skalierbare Hochleistungssimulationen
- <u>openfpm.mpi-cbg.de</u>

Programmierung: PPME

- Schnelle Softwareentwicklung
- <u>bitbucket.org/ppme/</u>

Echtzeitmikroskopie: ClearVolume

- Visualisierung während der Bildaufnahme
- https://github.com/clearvolume

Virtuelle Realität: Scenery

- Immersive Mikroskopie mit Nutzerinteraktion
- <u>https://github.com/clearvolume</u>/scenery

Scientific Computing for Systems Biology

Research Topics @MOSAICgroup1

- Scientific Computing: multiscale numerical simulation algorithms that can handle biological complexity
 —> Particle Methods
- Computer Graphics (with Prof. Gumhold and Prof. Dachselt): real-time VR of distributed 3D microscopy and simulation data
- Computer Vision: bio-image segmentation using particles, motion tracking
- High-Performance Computing: PPM Library, OpenFPM
- Programming languages and Compilers (with Prof. Castrillon): PPML
- Theory (with Prof. Baader): Automata and information theory of cellular and biochemical information processing

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