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Equation-free Modeling For Complex Systems *or* Enabling Microscopic Simulators to perform System Level Tasks or Solving Differential Equations Without the Equations Or A Systems Approach to Multiscale Simulations

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- or lemmings falling off a cliff

SIMULATION RESULTS



SIMULATION RESULTS



Loose thoughts

about multiscale /complex systems and their modeling

- Our example: interaction of many "units" between themselves and with their environment ----"emergent" behavior.
- "Physics" at a *fine* level, questions asked at a coarse-grained level

 This kind of complexity vs. The complexity of a commercial airliner

- Is laminar fluid flow "simple" ?
- Two billiard balls colliding elastically "simple" or "complex" 2

Multiscale / Complex System Modeling

"Textbook" engineering modeling: macroscopic behavior *through* macroscopic models (e.g. conservation equations augmented by closures)

Alternative (and increasingly frequent) modeling situation:

- Models
 - at a FINE / ATOMISTIC / STOCHASTIC level

MD, KMC, BD, LB (also CPMD...)

- Desired Behavior
 - At a COARSER Macrosconic Level

What I will tell you:

Solve the equations WITHOUT writing them down.

Write "software wrappers" around "fine level" microscopic codes

Top level:all algorithms we know and love (e.g. AUTO)Bottom level:MD, kMC, LB, BD, heterogeneous/ discrete media,
CPMD, hybrid

INTERFACE:

Trade Function Evaluation for "on demand" experimentaton and estimation

Think of the microscopic simulator AS AN EXPERIMENT That you can set up and run at will

"Equation Free" (motivated by "matrix free iterative linear algebra")
 Algorithms (coarse integration, patch dynamics, coarse RPM...)
 Tasks (stability/ bifurcation, control, optimization, dynamic renormalization)
 Examples (LB, KMC, BD, MD), and some nebulous thoughts



not with the EQUATION, but with the (computational) EXPERIMENT

Look at the experiment & RESTART IT

Projective Integration - a sequence of outer integration steps based on inner simulator + estimation (stochastic inference)



Coarse Behavior





RESTRICTION - a *many-one* mapping from a high-dimensional description (such as a collection of particles in Monte Carlo simulations) to a low-dimensional description - such as a finite element approximation to a *distribution* of the particles.

LIFTING - a *one-many* mapping from low- to high-dimensional descriptions.

We do the step-by-step simulation in the high-dimensional description.

We do the macroscopic tasks in the low-dimensional description.

SIMULATION RESULTS



Coarse projective integration: Accelerating things



THE CONCEPT: What else can I do with an integration code ?



"Coarse" Bifurcations



The Bifurcation Diagram



The Bifurcation Diagram

50000 agents, g=35, $\epsilon^+=0.075$, $\epsilon^-=-0.072$, $v_0^+=v_0^-=20$ Open loop response. From unstable to stable markets



The Bifurcation Diagram

50000 agents, g=35, ϵ^+ =0.075, ϵ^- = -0.072, v_0^+ = v_0^- = 20

Open loop response. Blow up



Multiscale Modeling Challenges:



Proposal: detailed modeling in small spatial boxes with interpolation between boxes - the "gap-tooth scheme"

Gap-Tooth Scheme



Ways to impose "coarsely inspired" boundary conditions Motivated from Li & Yip, 1998: Kevrekidis et al., nlin.CD/0302055 at arXiv.org Gear, Li and Kevrekidis, physics/0303010 at arXiv.org / PLA

Multiscale Modeling Challenges:



Can we combine gap tooth with projective integration in time?



Viscous Burgers equation: kMC Realization





STABILIZING UNSTABLE M**S**

Feedback controller design

We consider the problem of stabilizing an equilibrium x^* , p^* of a dynamical system of the form

 $\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), p(t)) \mathbf{f}: \mathbb{R}^{N} \times \mathbb{R} \rightarrow \mathbb{N}$

To do this the dynamic feedback control law is implemented:

 $p = p^* + K(x + Dw)$

where f and hence x^* is characterized of uncertainty

Where w is a M-dimensional variable that satisfies

 $\dot{w} = x + Dw$

Choose matrices **K**, **D** such that the closed loop system is stable

 $\dot{w} = 0, \ \dot{x} = 0 \qquad \rightarrow \qquad p = p^*$ and the system is stabilized in it's At steady state: "unknown" steady state $p = p^*, x = x^*$

In the case under study the control variable is the exogenous arrival frequency of "negative" information v_{ex} and the controlled variables the coefficients of the orthogonal polynomials used for the approximation of the ICDF

$$p = p^{n} + \mathbf{\Lambda} (\mathbf{x} + \mathbf{x})$$

STABILIZING UNSTABLE MARKETS

Control variable: the exogenous arrival frequency of "negative" information v_{ex}



<u>SIAM– July, 2004</u>

Clustering and stirring in a plankton model

Young, **<u>Roberts</u>** and Stuhne, *Nature* 2001

Dynamics of System with convection



Simulation Method

- Random (equal) birth and death, probability: $\lambda = \chi_{k}^{\prime} = x_{k} + \delta x_{k}(t); \langle \delta^{2} x_{k} \rangle = 2\tau D$
- Brownian motion. $x_k(t+\tau) = x'_k(t) + U^{\tau/2} \cos[ky'_k(t) + \varphi(t)]$ Advective stirring. $(\varphi, \theta \text{ are random } phases)$

$$G_t = 2D\frac{1}{r}(rG_r)_r + 2(\lambda - \mu)G + \gamma \frac{1}{r}(r^3G_r)_r + 2\lambda C\delta(\mathbf{r})$$

 IC: 20000 particles randomly placed in 1*1 hov

Stirring by a random field (color = y)



Dynamics of System with convection



Projective Integration: From t=2,3,4,5 to 10



Mapping $g_0(r) - Lifting$

- 1. From any system, check to find interval $[r_m, r_{m+1})$, s.t. max $|g(r)/g_0(r)-1|$.
- 2. if $g(r) > g_0(r)$, remove the atom with the largest contribution to g(r), and place it randomly inside box.
- 3. if $g(r) < g_0(r)$, select atoms *i*, *j*, st $r_{ij} > r_m$ and contribute the least to g(r). Remove the less crowded atom between i and j, and place it at the distance of $[r_m, r_{m+1})$ from the other.

Comparison of actual system and *lifted* system based on



Fixed Point Calulation Using Newton-Raphson (2-parameters)

Iteration	Area	X Scale	Error
0	12.48	0.83	1.57
1	13.96	0.81	1.05
2	15.69	0.79	0.32
3	15.38	0.80	0.05

NLDbyMDofH2OinCNT

Water Confinement in Carbon Nanotube Molecular Channels

Model system for studying H₂0 transport in channel pores of membrane proteins

Classical Molecular Dynamics (MD)

- Flexible CNT (L = 13.5 Å; R = 8.1
 Å)
- Graphite parameters
- 1034 TIP3P water molecules
- AMBER 6.0
- Particle-mesh Ewald electrostatics
- Gerhard Hummer



G. Hummer, J. C. Rasaiah, and J. P. Noworyta, Nature **414**, 188-190 (2001)

Filling-Emptying Transition of H₂O in CNT



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Effect of CNT-Water Attraction (λ) on Pore Hydration





- Constrain for τ = 15 ps and sample configurations: τ > 10 ps
- Initialize replicas: velocities from Maxwell-Boltzmann distribution

Solving for the Branches



Solve by Newton-Raphson $\frac{dN}{dt} = 0 \iff N - \Phi(N, \lambda) = 0$

$$\underline{J} = \left[1 - \frac{\partial \Phi(N, \lambda)}{\partial N}\right]$$

$$\frac{d\langle N \rangle}{dt} \approx -\frac{D(\langle N \rangle)}{k_B T} \frac{\partial G(\langle N \rangle)}{\partial \langle N \rangle} = F(N,\lambda)$$
$$\frac{\partial G}{\partial N} = 0 \qquad \frac{dN}{dt} = 0 \iff N - \Phi(N,\lambda) = 0$$

- 1. Set parameter (λ) ; specify coarse initial condition (N)
- 2. "Lifting": constrained MD
- 3. Let 50 replicas "free" for $\tau = 1 \text{ ps}$
- 4. Estimate Φ(N,λ) and J(N,λ)
 (Jacobian) (central differences for derivatives)
- 5. Do NR iterations; estimate new N
- 6. Go to (2) and repeat

$$\frac{\partial \Phi}{\partial N}\Big|_{N_k} = \frac{\Phi(N_k + \Delta N_k, \lambda) - \Phi(N_k - \Delta N_k, \lambda)}{2\Delta N_k}$$



Effective Free Energy Profiles: First Order Phase Transition

λ	Δ G		
0.725	4.354		
0.750	2.583		
0.7864	-0.0758		
0.7854	-0.0096		

 λ = 0.7250; βΔG = 4.355 12 λ = 0.7500; βΔG = 2.583 λ = 0.7864; βΔG = -0.0758 10 λ = 0.7854; βΔG = -0.0096 β⁶(N) 4 2 0 2 3 0 5 6 7 1 4 Ν

Solve $\Delta G(\lambda) = 0$ NR: $\lambda_1 = \lambda_0 - \Delta G(\lambda = \lambda_0) / \Delta G'(\lambda)|_{\lambda 0}$ $\Delta G'(\lambda)|_{\lambda 0} = (\Delta G(\lambda_0 + d\lambda) - \Delta G(\lambda_0)) / d\lambda$

- With $\lambda = 0.7864 \Rightarrow CMD$ for G(N)
- Fit quadratic for first 3 data points and estimate λ = 0.7854
- With $\lambda = 0.7854 \Rightarrow CMD$ for G(N)
- Fit quadratic again no change in fit; estimated λ = 0.7853

Kinetics of Filling-Emptying Transitions

Average transition time for system to go from completely filled state to empty state

$$\tau \approx \frac{2\pi}{\overline{D}\sqrt{\beta\Phi''(N_{\min})}\beta\Phi''(N_{saddle})} e^{\beta\Delta G_{\min \Leftrightarrow saddle}}$$
$$\overline{D} = \frac{1}{2} \left(D(N_{\min}) + D(N_{saddle}) \right)$$

	λ	τ _{Fulll→Empty} (ps)	τ _{Empty→Full} (ps)	Method	
	0.7854	~ 125	~ 126	CMD	
	0.750	~ 183	~ 2680	CMD	
	0.7517	230 ± 70	2400 ± 700	Eqblm. MD	
Eqblm.	MD: 15 emp	ying transitions (Ful	$II \rightarrow Empty$); 14 filling	transitions (Empty	∍ Full)
			,	1	1

Consider states inside CNT 00000
$$\stackrel{k_1}{\Leftrightarrow}_{k_2}$$
 11111 $k_1 = \frac{1}{\tau_{empty \rightarrow full}}; k_2 = \frac{1}{\tau_{full \rightarrow empty}}$
Relaxation time between filled and empty states $=\frac{1}{k_1 + k_2} \approx 171 \text{ ps}$

Relaxation time from coarse propagators: 165 ps



We are studying the accuracy and stability of these methods

And so all our algorithms for computing stable manifolds can be used (in conjunction with coarse timesteppers and RI

to approximate low-dimensional free energy surfaces !

ALTERNATIVE Mathematics – inspired ENSEMBLES

The Oseberg Transition Johnson, Jolly & K. IJBC 2001



Rare Events: Escaping from stability

Open loop response, g = 45.8



Computer-Aided Analysis of Nonlinear Problems in Transport Phenomena

Robert A. Brown, L. E. Scriven and William J. Silliman

in HOLMES, P.J., New Approaches to Nonlinear Problems in Dynamics, 1980

<u>ABSTRACT</u> The nonlinear partial differential equations of mass, momentum, energy, Species and charge transport.... can be solved in terms of functions of limited differentiability, no more than the physics warrants, rather than the analytic functions of classical analysis... basis sets consisting of low-order polynomials. systematically generating and analyzing solutions by fast computers employing modern matrix techniques.

..... nonlinear algebraic equations by the Newton-Raphson method. ... The Newton-Raphson technique is greatly preferred because the Jacobian of the solution is a treasure trove, not only for continuation, but also for analysing stability of solutions, for detecting bifurcations of solution families, and for computing asymptotic estimates of the effects, on any solution, of small changes in parameters, boundary conditions, and boundary shape.....

In what we do, not only the analysis, but *the equations themselves* are obtained on the computer, from short experiments with an alternative, microscopic description.

Coming full circle

No equations ?

Isn't that a little medieval ? Equations = "Understanding", right ?

AGAIN matrix free iterative linear algebra

 $\mathbf{A} \mathbf{x} = \mathbf{b}$

PRECONDITIONING, B A x = B b

B approximate inverse of A

Use "the best equation you have"

to *precondition* equation-free computations.

With enough initialization authority:

equation free *laboratory experiments*