Parallel Solution of Multiscale Stochastic Chemical Kinetics



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Overview

- Stochastic chemical kinetics: the what and the why
- Multiple scales: a hierarchy of models/solution methods
- The mesoscopic model; master equation/jump SDE
 - -Poisson random measure and nonlinear noise
- The parareal algorithm
- Combined scales in parallel
 - -Convergence and homogenization
- Example: stochastic toggle switch
- Example: homogenization of disparate rates
- Conclusions

$\begin{array}{c} \text{System size } \Omega \\ \text{($\#$ molecules)} \end{array}$	Model	Name
$\gtrsim 10^6$	ODE	Macroscopic
$\sim 10^4 - 10^8$	SDE (Langevin)	Mesoscopic (continuous)
$\sim 10^1 - 10^6$	jump SDE (master equation)	Mesoscopic (discrete)
$\lesssim 10^2$	Brownian dynamics (BD)	Microscopic

Model	Assumption	
BD	Brownian motion of individual molecules	
jump SDE	Non-individual, (locally) well-stirred	
SDE	Continuous approximation	
ODE	Continuous, deterministic	

The chemical master equation (Gardiner, van Kampen)

State vector $x \in \mathbf{Z}_{+}^{D}$ counting the number of molecules of each of D species; R specified reactions defined as transitions between the states,

$$x \xrightarrow{w_r(x)} x - \mathbb{N}_r, \qquad \mathbb{N} \in \mathbf{Z}^{D \times R} \ (stoichiometric \ matrix)$$

where each propensity $w_r: \mathbf{Z}_+^D \to \mathbf{R}_+$. The master equation is

$$\frac{\partial p(x,t)}{\partial t} = \sum_{r=1}^{R} w_r(x+\mathbb{N}_r)p(x+\mathbb{N}_r,t) - \sum_{r=1}^{R} w_r(x)p(x,t).$$

- -Discrete PDE in D dimensions for the probability density p.
- -Several simulation algorithms exist (SSA, NRM, ...).

The jump SDE (Plyasunov '05, Li '07, Ikeda/Watanabe, Gihman/Skorohod)

- -Probability space $(\Sigma, \mathbf{F}, \mathbf{P})$.
- -The Poisson random measure: $\mu(dt \times dz; \sigma)$, $\sigma \in \Sigma$; an increasing sequence of arrival times $\tau_i \in \mathbf{R}_+$ with random "marks" z_i uniformly distributed in $[0, \overline{W}]$. Deterministic intensity is $m(dt \times dz) = dt \times dz$.
- -Closed system: $\bar{W} := \sum_r \max_x w_r(x)$.
- -Open system: $\overline{W}(t) = \sum_r w_r(X(t))$ (state-dependent intensity).

$$dX_t = -\sum_{r=1}^R \mathbb{N}_r \int_0^{\bar{W}} \hat{w}_r(X(t-); z) \,\mu(dt \times dz)$$

$$= -\sum_{r=1}^{R} \mathbb{N}_r w_r(X(t-)) dt - \sum_{r=1}^{R} \mathbb{N}_r \int_0^{\bar{W}} \hat{w}_r(X(t-); z) (\mu - m) (dt \times dz).$$

-Where the \hat{w}_r are indicator functions (a thinning of the measure).

The basic idea... (Lions/Maday/Turinici '00, Staff '03, Bal '06)

$$\dot{u} = -Au, t \in [0, T]$$
 with some $u(0) = u_0$.
 $\mathcal{F}_t(y) \equiv y - \int_0^t Au(t) dt$ where $u(0) = y$, and,
 $\mathcal{C}_t \approx \mathcal{F}_t$ but faster!

Discretize time in $N = T/\Delta t$ chunks. Any solver $S \in \{\mathcal{F}_{\Delta t}, \mathcal{C}_{\Delta t}\}$ can be used to compute a numerical solution:

$$B(S)v = \begin{bmatrix} I & 0 & 0 & 0 \\ -S & I & 0 & 0 \\ 0 & -S & I & 0 \\ 0 & 0 & -S & I \end{bmatrix} \begin{bmatrix} v_0 \\ v_1 \\ v_2 \\ v_3 \end{bmatrix} = \begin{bmatrix} u_0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = u_0.$$

Parareal is the fix-point iteration obtained by using $B(\mathcal{C}_{\Delta t})^{-1}$ as an approximate inverse to $B(\mathcal{F}_{\Delta t})$:

$$v_{k+1} = v_k - B(\mathcal{C}_{\Delta t})^{-1} (B(\mathcal{F}_{\Delta t}) v_k - u_0).$$

Let $v_{0,0} = u_0$ and $v_{0,n} = \mathcal{C}_{\Delta t} v_{0,n-1}$ to start up the algorithm. Then

$$v_{k,n} = \mathcal{F}_{\Delta t} v_{k-1,n-1} - [\mathcal{C}_{\Delta t} v_{k-1,n-1} - \mathcal{C}_{\Delta t} v_{k,n-1}],$$

where the expensive evaluation of \mathcal{F} is trivially parallel.

-In fact, the algorithm is *strictly* parallel (serial version is pointless).

Convergence results

- -Setup: use for C the macroscopic ODE (rate equations), and use a stochastic simulation technique for F.
- -The RMS-error

$$\left(E[\tilde{X}_{k,n} - X_n]^2\right)^{1/2} \le C_{1,T} S_{\mathcal{F}}^k
\le C_{2,T} M^{2^{-k}} \text{ (nonlinear transient)},$$

where $S_{\mathcal{F}} \propto \sqrt{L}$ (total Lipschitz constant) and where M is the initial RMS-error.

-(Very) weak error:

$$|E[\tilde{X}_{k,n} - X_n]| \le C_{3,T} \Delta t^{k/2}.$$

Homogenization

- -Ultimately, the convergence depends rather strongly on the Lipschitz constant! The reason is the lack of sufficiently high order (strong) consistency of \mathcal{C} w.r.t. \mathcal{F} .
- -For stiff models one is often interested in seeking an effective slow dynamics. A way to achieve this is to replace \mathcal{F} with a homogenized version \mathcal{F}^h ;

$$\mathcal{F}^h X_0 := \frac{1}{\delta t} \int_{\Delta t - \delta t}^{\Delta t} Y(t) dt$$
, where $Y(t) = \mathcal{F}_t X_0$,

- $-\delta t$ large enough to contain several fast reactions but short enough to be essentially independent on the slow scales.
- -Again, this homogenization is strictly parallel.

Stochastic toggle switch

Biological 'transistor' in the regulatory network of *E. coli*:

$$\begin{pmatrix}
\emptyset & \frac{a/(b+y^2)}{\longrightarrow} & X & \emptyset & \frac{a/(b+x^2)}{\longrightarrow} & Y \\
X & \frac{\mu x}{\longrightarrow} & \emptyset & Y & \frac{\mu y}{\longrightarrow} & \emptyset
\end{pmatrix}$$

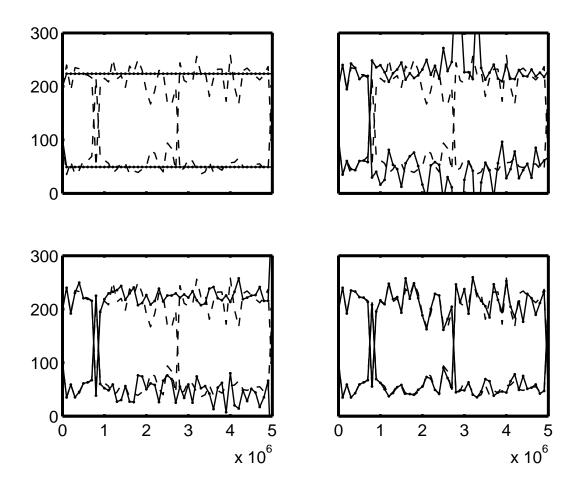


Figure 1: Solid: parallel solution after 0, 1, 2 and 4 iterations.

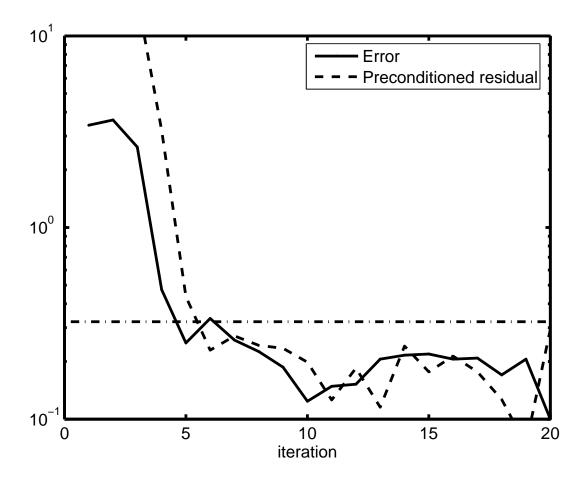


Figure 2: Dash-dot: propensities perturbed by $\pm 1\%$.

Homogenization of disparate rates

Fast dimerization/slow isomerization:

$$X_{1} + X_{1} \stackrel{1/\varepsilon}{\rightleftharpoons} X_{2} + X_{2}$$

$$X_{2} \stackrel{1}{\rightleftharpoons} Y_{2}$$

$$Y_{2} + Y_{2} \stackrel{1/\varepsilon}{\rightleftharpoons} Y_{1} + Y_{1}$$

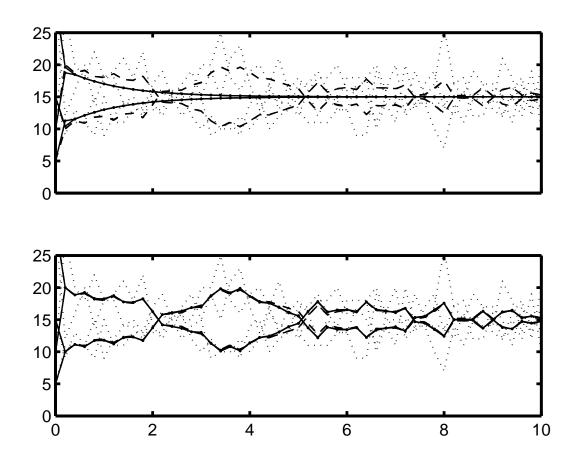
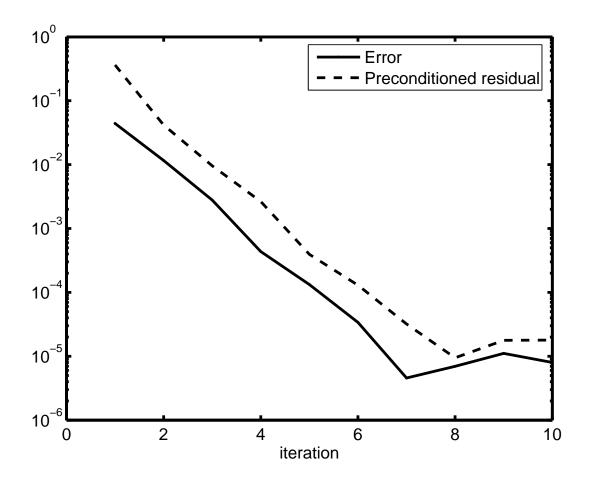


Figure 3: Original (dot) and homogenized (dash) trajectories. In solid: parallel solution (0 and 1 iteration).



Conclusions

- Mesoscopic stochastic kinetics (jump SDE/master equation): (locally) well stirred chemical reactions
 -macroscopic limit: nonlinear ODE/(reaction-diffusion PDE)
- Parareal combination jump SDE/ODE -RMS-convergence depends on the Lipschitz constant -convergence of the first moment as $\Delta t \to 0$
- Homogenization in parallel: homogenized solution rather than a homogenized equation generalizes to other types of SDEs
 -parareal applied to stiff stochastic equations (previously unclear)
- A fix number of parareal iterations can be thought of as a stochastic/deterministic hybrid with very few parameters
- Yet to do: better efficiency through multilevel parallelism, analysis of open system