Kharagpur Lectures

Numerical Accuracy, Error Control and Applications

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Second-Order Symplectic Integration Algorithms Harmonic oscillator : $\dot{q} = p$; $\dot{p} = -q$; $(q, p)_0 = (1, 0)$ Solve one second order equation or two first order equations : $\frac{d^2x}{dt^2} = F(x)$ $\frac{dx}{dt} = \mathbf{v}; \frac{d\mathbf{v}}{dt} = F(x).$ Störmer-Verlet . Leapfrog ; 3 stages . $x_{n+1} = 2x_n - x_{n-1} + dt^2 F(x_n)$ $x_n = x_{n-1} + v_{n-(1/2)} dt$; $a_n = F(x_n) ;$ $\mathbf{v}_{n+(1/2)} = \mathbf{v}_{n-(1/2)} + a_n dt$. The Stormer-Verlet difference equation can be solved analytically : $q_0 = e^{i\omega 0}; q_{+1} = e^{i\omega dt}; q_{-1} = e^{i\omega(-dt)};$ $\omega = (1/dt) \ cos^{-1}(1 - dt^2/2)$ Then $q \, error = max \left(\sqrt{(cos(time) - cos(\omega j dt))^2} \right)$ Wm. G. Hoover and Carol G. Hoover, "Comparison of Very Smooth Cell-Model Trajectories", ariXiv:1504.00620.



Fourth-Order Symplectic Algorithm (Candy and Rozmus) The fourth-order symplectic algorithms solve first order differential equations. The number of stages in a timestep is four $\dot{q} = p$; $\dot{p} = F$ Specify q_0 and p_0 ; $q_i = q_{i-1} + a_i p_{i-1} dt$; $p_i = p_{i-1} + b_i F_i dt$; for i = 1, 4 $a_1 = a_4 = (2 + 2^{1/3} + 2^{-1/3})/6$; $b_1 = b_3 = (2 - 2^{1/3})^{-1}$ $a_2 = a_3 = (1 - 2^{1/3} - 2^{-1/3})/6$; $b_2 = (1 - 2^{2/3})^{-1}$. Q = Q + a1*P*dtP = P + b1*F*dtProgramming steps : Q = Q + a2*P*dtP = P + b2*F*dtQ = Q + a2*P*dtP = P + b1*F*dtQ = Q + a1*P*dtStephen K. Gray, Donald W. Noid and Bobby G. Sumpter, "Symplectic integrators for large scale molecular dynamics: A comparison of several explicit methods", J. Chem. Phys., Vol. 101, (September 1994).



Runge-Kutta Methods					
Fourth-Order Runge-Kutta Method					
1. Four steps calculate approximate derivatives :					
 Calculate new values of v and F using updated values of x and p (right-hand-side evaluation) Update x and v for dt/2 or dt. 					
 Calculate updated values of x and v over the full time step using a weighted average of the derivatives computed in the previous four-step calculation. 					
Fifth-Order Runge-Kutta Method					
 Six update steps to calculate approximate derivatives . Some update steps use weighted derivatives . 					
2. Final step uses a weighted average of six approximate derivatives .					



Storage Layout for the Runge-Kutta Algorithms 5 particles				
YY Arrav	YYP Array			
Position and Momenta	Derivatives			
x1 = yy(1)	yyp(1) = p1			
x2 = yy(2)	yyp(2) = p2			
x3 = yy(3)	yyp(3) = p3			
x4 = yy(4)	yyp(4) = p4			
x5 = yy(5)	yyp(5) = p5			
p1 = yy(6)	yyp(6) = f1			
p2 = yy(7)	yyp(7) = f2			
p3 = yy(8)	yyp(8) = f3			
p4 = yy(9)	yyp(9) = f4			
p5 = yy(10)	yyp(10) = f5			











	A Comparison of Integration Methods for the Cell Model						
	Method	Order	Accurate Trajectory Time	Energy Accuracy	Reversal Time	Force Evaluations	
	Leapfrog	2 nd	18	10 ⁻⁷	47	1	
ic	Candy Rozmus	4 th	34	10 ⁻¹⁵	42	3	
Symplect	Monte Carlo	4 th	31	10 ⁻¹³	43	5	
	Yoshida	6 th	36	10 ⁻¹⁵	42	7	
	Runge- Kutta	4 th	35	10 ⁻¹³	42	4	
	Runge- Kutta	5 th	34	10 ⁻¹⁵	42	6	

Accurate trajectory time occurs for coordinate errors less than 0.01 compared to 8^{th} order Telroy-Schlier-Sieter symplectic method. Coefficients are extended precision . Here dt = 0.001, a typical MD timestep



3. Predictor – Corrector Methods
 Used for stiff equations Often stiff equations arise for problems with two time scales in the solution Two steps : The Predictor step is explicit The Corrector step is implicit Predictor-Corrector schemes are not self-starting Fourth and fifth order Runge-Kutta algorithms are self-starting ! Combining the two Runge-Kutta algorithms results in an excellent adaptive integrator for the Nosé oscillator Second Order Störmer-Verlet is self starting Stability is important ** Stable time steps are usually larger for implicit than for explicit algorithms Molecular dynamics : Nosé's thermostated oscillator Continuum mechanics : Viscoplasticity and other nonlinear effects Other examples include chemical reactions with two time scales, and circuit analysis Milne's two methods can be analyzed with the Harmonic Oscillator.
 Milne's two methods can be analyzed with the Harmonic Oscillator. The first uses the two first order equations of motion and the second uses the second order equation of motion
** For more details on implicit methods see the following :
http://qucs.sourceforge.net/tech/node25.html http://qucs.sourceforge.net/tech/node24.html



Predictor-Corrector Algorithms are not Self-Starting

If the analytical form of the solution is known, it can used to evaluate nearby points to start up the algorithm .

Taylor's series can always be used to generate the extra points needed to start the algorithm . This can also be done numerically .

Evaluate the function and its derivative each at two nearby points. This is the finite difference technique .

Accuracy can be evaluated using analytical solutions for the numerical approximation and comparing the error when the time step in reduced in a systematic way .

Student problem

Any of the algorithms can be evaluated with the oscillator .

Is the stability behavior different when using previous points versus future points in Taylor series ?



Gear Predictor-Corrector Method					
$r_{t+dt}^p = r_t + dt(v_t) + \frac{dt^2}{2}a_t + \frac{dt^3}{6}b_t + \cdots$					
$v_{t+dt}^p = v_t + dt(a_t) + \frac{dt^2}{2}b_t + \cdots$					
$a_{t+dt}^p = a_t + dt(b_t) + \cdots$					
$b_{t+dt}^p = b_t$ Predictor Step					
$ \begin{pmatrix} r \\ v \\ a \\ b \end{pmatrix}_{t+dt}^{p} = \begin{pmatrix} 1 & dt & \frac{dt^{2}}{2} & \frac{dt^{3}}{6} \\ 0 & 1 & dt & \frac{dt^{2}}{2} \\ 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} r \\ v \\ a \\ b \end{pmatrix}_{t} ; \qquad r_{t+dt}^{p} \to a_{t+dt}^{c} ; \\ \Delta a_{0} = (a_{t+dt}^{c} - a_{t+dt}^{p}) dt^{2}/2 $					
Corrector Step					
$\binom{r}{\binom{v}{a}}_{t+dt}^{c,0} = \binom{r}{\binom{v}{a}}_{t+dt}^{p} + (c_0 + c_1 + c_2 + c_3)\Delta a_0 \binom{1}{\frac{1/dt}{2/dt^2}}_{6/dt^3}; (c_1, c_2, c_3, c_4) = \left(\frac{1}{6}, \frac{5}{6}, 1, \frac{1}{3}\right)$					
Student Problem					
Consult Gear's book for a fourth order gear algorithm with an iteration scheme for the corrector step.					
Gear, G. W., <i>Numerical Initial Value Problems in Ordinary Differential Equations</i> , Prentice-Hall, Englewood Cliffs, N. J. (1971).					

Gear Algorithm with a single iteration of the Corrector Step c Gear algorithm for the harmonic oscillator do it = 1,itmax c predictor ro = 1.0d00 ! initial condition rp = ro + dt*vo + 0.5d00*(dt**2)*ao + vo = 0.0d00 & (1.0d00/6.0d00)*(dt**3)*bo vp = vo + dt*ao + 0.5d00*(dt**2)*bo & ao = -1.0d00 vp = vo + dt * ao + 0.5d00 ap = ao + dt * bo bp = bo ac = -rp dela = (ac - ap) DA = 0.5d00*dela*dt*dtbo = 0.0d00 dt = (1/2)**n ! Pick dt for n = 1,9 rp = 0.0d00! Predictor values vp = 0.0d00ap = 0.0d00bp = 0.0d00c corrector rc = rp + c0*DAvc = vp + c1*DA/dtvc = vp + c1*)A/dt ac = ap + 2.0d00*c2*DA/(dt**2) bc = bp + 6.0d00*c3*DA/(dt**3) time = it*dt Ham = 0.5d00*(rc**2 + vc**2) rc = 0.0d00! Corrector values vc = 0.0d00ac = 0.0d00bc = 0.0d00write(6,*)time, rc, vc, ac, bc, Ham time = 0.0d00ro = rc ! reset the variables vo = vc Ham = 0.5d00*(ro**2 + vo**2)ao = acbo = bcHam0 = Ham write(6,*)"energy ",time,Ham end do c0 = 1.0d00/6.0d00c1 = 5.0000/6.0000c2 = 1.0000c3 = 1.0d00/3.0d00

Table E.I	Gear correc	tor coeffic			A attation	
Values	Co	C,	C2	ca	equation C.	<i>C</i> •
				-,		
3	5/12	1	1/2			
4	3/8	1	3/4	1/6		
5	251/720	1	11/12	1/3	1/24	
6	95/288	1	25/24	35/72	5/48	1/120
Table E.2 Values	Gear correct	tor coeffic c ₁	c ₂	c ₃	er equation	c5
Table E.2 Values	Gear correct	tor coeffic c ₁ 1	$\frac{c_2}{1}$	c ₃	er equation c4	c ₅
Table E.2 Values 3 4	Gear correct	tor coeffic c ₁ 1 5/6	ients for a c_2 1 1	c ₃	er equation c4	c5
Table E.2 Values 3 4 5	Gear correct	tor coefficient c_1 c_1 1 5/6 3/4	<i>c</i> ₂ 1 1 1	c ₃	er equation c4 1/12	c5

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The Thermostated Harmonic Oscillator

The Nosé oscillator is the motion of a harmonic oscillator with a specified average temperature ! Nosé's idea (1984) was to replace isoenergetic mechanics with a temperature-based mechanics. To do this he developed a temperature dependent Hamiltonian consistent with Gibbs' canonical distribution. When this Hamiltonian is applied to the harmonic oscillator the resulting equations of motion are very stiff !

$$2\mathcal{H} = q^2 + p^2/s^2 + \mathrm{Tln}(s^2) + \zeta^2 \equiv \mathbf{0} \rightarrow$$

Nosé Oscillator Equations

$$\dot{q} = (p/s^2); \ \dot{p} = -q; \ \dot{s} = \zeta; \ \dot{\zeta} = (p^2/s^3) - 1/s$$

for $\kappa, T, k, m = 1$.

Dettmann and Morris later modified the original Nosé Hamiltonian and showed that the following Nosé-Hoover equations (Hoover 1985) can be derived from it.

Nosé-Hoover Oscillator Equations

$$\dot{q} = p/s$$
; $\dot{p} = -sq$; $\dot{s} = s\zeta$; $\dot{\zeta} = p^2/s^2 - 1$ #1
 $p/s \rightarrow p$; $\dot{q} = p$; $\dot{p} = -q - \zeta p$; $\dot{\zeta} = p^2 - 1$. #2



The unusual aspect of these two oscillators is that the two trajectories are exactly the same but the dynamical rates of progress along the common trajectory are different. This is referred to as "time scaling" in Nosé's original paper. We will show that this is the cause of the numerical stiffness !



- In mathamatics, a stiff equation is a differential equation for which the usual numerical methods for solving the equation are numerically unstable, unless the step size is taken to be extremely small.
- Adaptive methods can be used in some cases to overcome numerical instability. We will illustrate this with the Nosé oscillator example .
- Adaptive methods cannot be used for singular integrands such as the "event-driven" hard sphere collision models.
- Other examples of numerical stiffness arise in problems with two time scales as in circuit analysis. In these cases the stiffness is treated with predictor-corrector methods including implicit methods. Matrix solutions are required for the implicit methods.
 - Most molecular dynamics motion equations are solved with explicit techniques !





















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Energy must be conserved in a Hamiltonian System !

Error in the Hamiltonian

S	Double precision	Quadruple precision		
0.062500	-3.2702049634902863E-05	-4.997996331072645417188952190057969E-13		
0.056135*	-3.3960281428768724E-05	9.510041726002260340923701275951037E-13		
0.031250	-3.3617859108492354E-05	-3.207674481318156868420757831612092E-11		

* This is the value that corresponds to a vanishing Hamiltonian .

Lyapunov Exponents and Chaos The instantaneous Lyapunov exponent measures the exponential growth of the separation of two nearby neighboring trajectories, $\dot{\delta} = \lambda \delta$. We choose a neighboring satellite trajectory x_s constrained a distance δ = 0.000001 from a reference trajectory x_r . After a time step dt, the distance is rescaled to δ providing a measure of the growth of separation during that interval. $x_r = x_r + g(x_s - x_r)$ where $g = \left(\delta/\sqrt{(x_s - x_r)^2}\right) \cong e^{-\lambda dt}$ $\longrightarrow \lambda(t) = -ln(g)/dt$ This instantaneous or local Lyapunov exponent averaged over a very long trajectory gives the Lyapunov exponent for the phase-space trajectory. $\lambda = \sum (\lambda(t)dt) / \sum (dt)$ This Lyapunov is the maximum of the four Lyapunov exponent measuring the growth in phase space for the oscillator. Bill will present algorithms for calculating the full spectrum in a later lecture. The solutions of the thermostated oscillator are characterized by the value of the maximum exponent :

 $\lambda > 0$ chaotic solution; $\lambda = 0$ conservative tori.









Analyzing the Results With Histograms

We can understand better the motion of the oscillators by looking at the probability density for the logarithm of the time scaling variable and the time steps.

• With a variable time step care must be taken in computing the

probability density for the time scaling variable ${\it S}$. A trajectory value,

 $ln(S_{traj})$, is associated with the *ith* bin if

$$\ln(s)_i \le \ln(s_{traj}) < \ln(s)_{i+1}$$

However, the probability that the trajectory values will fall into the bin is equal to the fraction of the time that the trajectory spends within the bin. Thus, the probability density in the ith bin is given by

$$p(\ln(s)_i \le \ln(s_{traj}) < \ln(s_{i+1}) = \sum_{i=1}^N \Delta t_i / \Sigma \Delta t_j$$

for 4 000,000,000 time steps .

The time-step histograms show that there were three values of dt used for the smooth Nosé-Hoover equations and more than 20 values of dt (a factor of a million) for the Nosé oscillator. All these time steps are adaptive .





Results and Conclusions: Adaptive Integration for Nosé and Nosé-Hoover Oscillators

- Nosé Oscillator can be treated with the Adaptive 4th-Order Runge-Kutta Algorithm
- The trajectories for the Nosé and Nosé-Hoover oscillators are the same but progress at different rates
- Trajectory intervals measured between two p = 0 sections show that the sections are identical for the two oscillators
- The time scaling variable provides the connection between the Lyapunov exponents for the two oscillators
- The local Lyapunov exponent is an important measure of stiffness
- We find linear correlations on log-log plots of the the momentum and time scaling versus time.













