

# *MAT351 - HW1 - Part 2*

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## 1 Problem 5: Wilson Exercise 5.1, p70, et al.

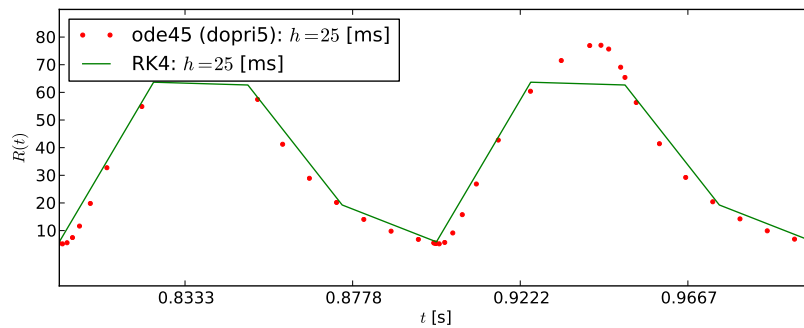


Figure 1: Adaptive timesteping vs widely-stepped RK4. Since Matlab's ODE45 and ODE15s algorithms, and SciPy's equivalent `dopri5` and `vode/bdf` actually don't do vanilla RK4, but a more sophisticated adaptive method, I thought it would be interesting to show this graphically. The same timestep is given to both solvers, but the `ode15s`-analog adaptively adds extra timesteps where the rate-of-change is high.

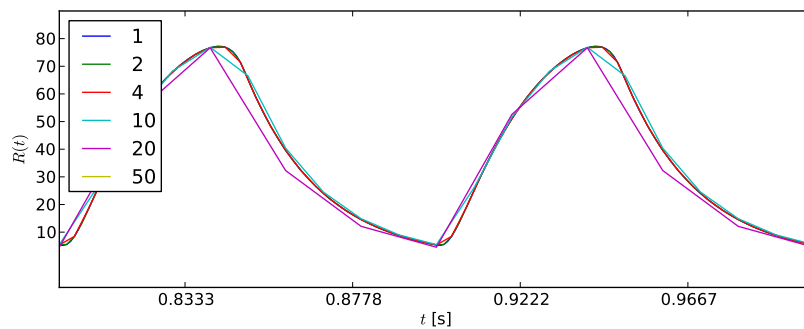


Figure 2: Wilson, problem 5.1. simple Naka-Rushton neuron via Runge-Kutta  $\mathcal{O}(4)$  time-integration. Only the last 0.20 [s] of integration time is shown. Legend gives timestep in [ms]. Analytical solution (not shown) for  $P(t) = 1$  (constant forcing) is  $R(t) = \frac{50}{13}(1 - e^{-50t})$

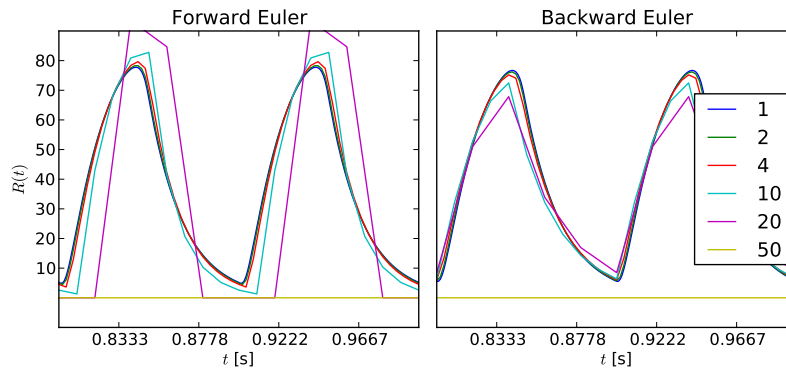


Figure 3: Naka-Rushton neuron via forward and backward Euler-integration. Only the last 0.20 [s] of integration time is shown. Legend gives timestep in [ms]. All but the largest of the timesteps seem to be in the domain of stability for backwards Euler for this problem.

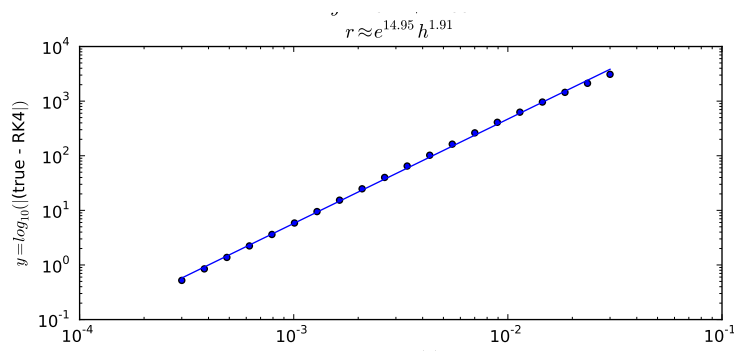


Figure 4: Growth of RK4 error as step-size  $h$  increases. Error is measured as the  $L_2$  norm of the difference between the solution for  $h = 10^{-5}$  [s] (assumed to be the “true” solution) and a linear interpolant of the solution  $R(t)$  for the given value of  $h$ . In contrast to the theoretical prediction of  $r \sim \mathcal{O}(4)$ , I regressed an exponent better than 2 for this problem (below the limiting  $h$  value where RK4 diverged). This is consistent, I think with the  $\mathcal{O}(4)$  estimate being an upper bound on the error.

'''

Hugh R. Wilson, "Spikes, decisions, and actions: dynamical foundations of neuroscience", chapter 5, problem 1

With additions from Holmes 323HW14.1.pdf, problem 5.

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'''

import numpy as np

import matplotlib.pyplot as plt

from Integrators import integrate, logging

def dXdt(X, t):

    R = X[0] # len(X) = 1

    P = 20. \* np.sin(np.pi \* 20 \* t)

    if P < 0:

        S = 0

```

else:
    S = 100. * P**2 / (25 + P**2)
    return np.array([(-R + S) / .02])

tf = 1.0

# First, a plot showing adaptive timesteping. Not that it was requested.
adapFig = plt.figure(figsize=(8.5,3.5))
adapAx = adapFig.add_subplot(1, 1, 1)
h = .025
for method, label, style in zip(
    ('ode45', 'rungekutta'),
    ('ode45 (dopri5)', 'RK4'),
    ('r.', 'g')):
    X, T = integrate(dXdt, h, t0=0.0, tf=tf, X0=(0.0,), method=method)
    adapAx.plot(T, X[0,:], style, label='%s: $h= %.0f$ [ms]' % (label, h*1e3))

# Now, Runge-Kutta 0(4) with various timesteps.
tstepFig = plt.figure(figsize=(8.5,3.5))
tstepAx = tstepFig.add_subplot(1, 1, 1)

hs = .001, .002, .004, .01, .02, .05
# To get something to compare against, we'll use a super-fine timestep and just
# hope that we don't get subtractive machine-precision error.

for h in hs:
    X, T = integrate(dXdt, h, 0.0, tf, (0.0,), method='rungekutta')
    tstepAx.plot(T, X[0:], label='%s' % (h*1e3))

# Let's explicitly look at the norm of the error
def linInterp(T, X, Treq):
    """
    Produce linear interpolation of X(T) at the requested T values
    """
    def findClosest(vec, val):
        """Return the index where vec[index] is closest to val.
        >>> findClosest([2, 8, 3, 6], 5)
        3
        """
        distances = np.abs([val - x for x in vec])
        return distances.tolist().index(np.min(distances))
    assert T[0] == Treq[0], 'I am lazy.'
```

```

j = 0
built = np.empty(Treq.shape)
for i in range(len(T) - 1):
    t1 = T[i]
    t2 = T[i + 1]

    while j < len(Treq) and t1 <= Treq[j] < t2:
        dxdt = (X[i+1] - X[i]) / (T[i+1] - T[i])
        built[j] = dxdt * (Treq[j] - T[i]) + X[i]
        j += 1

return built

errFig = plt.figure(figsize=(8.5, 3.5))
errAx = errFig.add_subplot(1, 1, 1)
trueSoln, trueTimes = integrate(dXdT, .00001, 0.0, tf, (0.0,)), method='rungekutta')
errs = []
hsErr = 3*np.logspace(-4, -2, 20)
for h in hsErr:
    logging.info('error plotting: h=%f' % h)
    X, T = integrate(dXdT, h, 0.0, tf, (0.0,)), method='rungekutta')
    interpolated = linInterp(T, X.ravel(), trueTimes)
    errs.append(np.linalg.norm(trueSoln[0, :] - interpolated))
errAx.scatter(hsErr, errs)
errAx.set_xlabel('$x=log_{10}(h)$')
errAx.set_ylabel('$y=log_{10}(|$(true - RK4$)|)$')
errAx.set_xscale('log')
errAx.set_yscale('log')
# fit a line:
from scipy.optimize import minimize
def minimizeThis(MB):
    m = MB[0]
    b = MB[1]
    #l10(err)0 = m * l10(h) + b
    return np.linalg.norm(m * np.log(hsErr) + b - np.log(np.asarray(errs)))
MB = minimize(minimizeThis, np.array([4,.001])).x
xlim = errAx.get_xlim()
ylim = errAx.get_ylim()
m, b = tuple(MB)
errAx.plot(hsErr, np.exp(b)*hsErr**m)
logging.info('m=%f, b=%f' % (m, b))
errAx.set_title(
    r'$y\approx$.2fx+.2f$' % (m, b) + '\n' +

```

```

        r'$r\approx e^{%.2f}h^{%.2f}$' % (b, m)
    )

showTime = 0.20 # We're not going to plot the whole thing.

# Now, forward/backward Euler with the same timesteps:
fbFig = plt.figure(figsize=(8.5,4))
ax2forward = fbFig.add_subplot(1, 2, 1)
ax2backward = fbFig.add_subplot(1, 2, 2)
for axis, method in zip(
    (ax2forward, ax2backward),
    ('Forward Euler', 'Backward Euler')
):
    axis.set_title(method)
    for h in hs:
        X, T = integrate(dXdt, h, 0.0, tf, (0.0,), method=method
                        .replace(' ', ''))
                        .replace('Forward', ''))
        axis.plot(T, X[0,:], label='%.0f' % (h*1e3))

# Fix up the plots a bit.
for axis in tstepAx, ax2forward, ax2backward, adapAx:
    d = showTime / 6
    maxy = 90
    miny = -10

    if axis is not ax2backward: # We'll do something different with this.
        axis.set_ylabel('$R(t)$')
        axis.set_yticks(np.arange(10, maxy, 10))
    else:
        axis.set_yticks([])
    axis.set_ylim(miny, maxy)

    axis.set_xlabel('$t$ [s]')
    axis.set_xticks(np.linspace(tf-showTime+d, tf-d, 4))
    axis.set_xlim(tf - showTime, tf)
tstepAx.legend(loc='upper left')
adapAx.legend(loc='upper left')
ax2backward.legend(loc='right')
fbFig.subplots_adjust(bottom=.14, top=.9, left=.1, right=.99, wspace=.05)
tstepFig.subplots_adjust(bottom=.18, top=.99, left=.08, right=.99)
adapFig.subplots_adjust(bottom=.18, top=.99, left=.08, right=.99)
errFig.subplots_adjust(top=.9)

```

```
# Save them.
tstepFig.savefig('hw1b-wils5_1.pdf')
fbFig.savefig('hw1b-5-forwardBackward.pdf')
adapFig.savefig('hw1b-5-adaptive.pdf')
errFig.savefig('hw1b-5-error.pdf')

# The analytical solution for P=1 is
#  $R(t) = \frac{50}{13}(1 - e^{-50t})$ 

# plt.show()
# from os import system; system('/usr/bin/notify-send done')
```

## 2 Problem 6: Numerical experiments on a nonlinear ODE

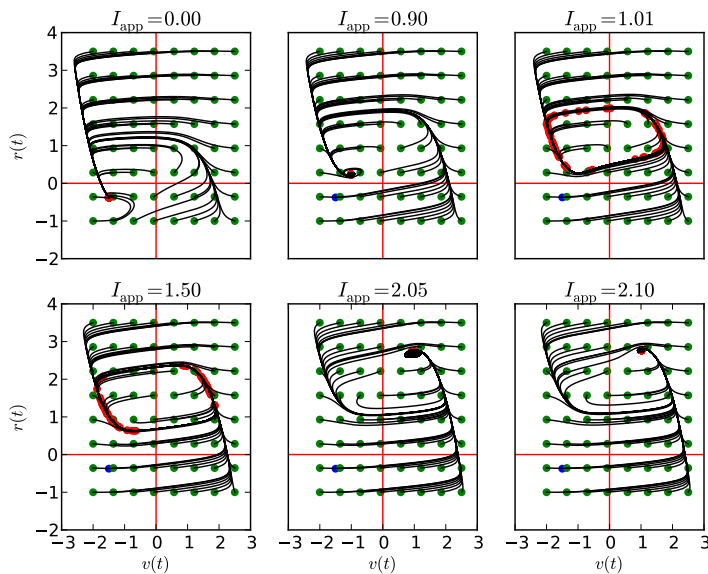


Figure 5: Partial phase portraits for a Fitzhugh-Nagumo neuron for several values of the applied-current parameter  $I_{app}$ . Green points are initial conditions; red are final (after 10 [s] of integration). As also happens in the Hodgkin-Huxley neuron, there is a lower and an upper steady state, separated from a stable limit cycle by a pair of Hopf bifurcations. For  $I_{app} = 0$ , the fixed point is at  $v = -\frac{3}{2}$ ,  $r = -\frac{3}{8}$ .

'''

Created on Feb 24, 2014, 3:58:19 PM

@author: bertalan

'''

```
import numpy as np
import matplotlib.pyplot as plt
from Integrators import integrate, logging
```

```
def FitzhughNagumo(Iapp):
    '''This closure gives the RHS function for a particular applied current value.'''
    def dXdt(X, t):
        '''t is not used (the ODE is autonomous)'''
        v = X[0]
        r = X[1]
        tv = .1
        tr = 1
        dvdt = (v - v**3 / 3 - r + Iapp) / tv
        drdt = (-r + 1.25 * v + 1.5) / tr
        return np.array([dvdt, drdt])
    return dXdt
```



```

fig = plt.figure()

Iapps = 0, 0.9, 1.01, 1.5, 2.05, 2.1
# for Iapp = 0, the fixed point is (-3/2, -3/8)
axes = []
for i in range(6):
    axes.append(fig.add_subplot(2, 3, i+1))

for ax, Iapp in zip(axes, Iapps):
    logging.info('Iapp=%f' % Iapp)
    dXdt = FitzhughNagumo(Iapp)
    ax.axhline(0, color='red')
    ax.axvline(0, color='red')
    ax.scatter(-3./2, -3./8, color='blue')
    for v0 in np.linspace(-2, 2.5, 8):
        # logging.info('v0=%s' % str(v0))
        for r0 in np.linspace(-1, 3.5, 8):
            X0 = v0, r0
            logging.info('X0=%s' % str(X0))
            # Uncomment these two lines to verify the Euler solution with RK4:
            #X, T = integrate(dXdt, .01, 0, 10.0, X0, method='rungekutta')
            #ax.plot(X[0,:], X[1,:], 'r.')
            X, T = integrate(dXdt, .01, 0, 10.0, X0, method='euler')
            ax.plot(X[0,:], X[1,:], 'k')
            ax.scatter(X[0,0], X[1,0], color='green') # the initial condition...
            ax.scatter(X[0,-1], X[1,-1], color='red') # ...and the final point
            ax.set_title('$I_{\mathrm{app}} = %.2f$' % Iapp)

for i in 0, 1, 2:
    axes[i].set_xticks([])
for i in 1, 2, 4, 5:
    axes[i].set_yticks([])
for i in 0, 3:
    axes[i].set_ylabel('$r(t)$')
for i in 3, 4, 5:
    axes[i].set_xlabel('$v(t)$')
for ax in axes:
    ax.set_xlim(-3, 3)
    ax.set_ylim(-2, 4)

ax.legend()

fig.savefig('hw1bp6-flows.pdf')

```

```
plt.show()
```

3 *Integrators.py*

```
'''
Created on Feb 24, 2014, 1:04:36 PM

@author: bertalan
'''

import numpy as np # Gives us matrices and linear algebra.
import logging
logging.basicConfig(format='%(levelname)s: %(message)s',
                    level=logging.INFO, # Turn on/off debug by switching INFO/ERROR.
                    name='log')

def integrate(dXdt, h, t0, tf, X0, method='euler', newtontol=1e-6):
    """
    Integrate the differential equation dXdt from t0 to tf in steps of size h,
    and initial condition X0. method can be one of 'euler', 'rungeKutta', or
    'backwardEuler'; not case-sensitive.

    If 'backwardEuler' is used, newtontol specifies the tolerance for the
    implicit solver.

    Returns the history of states and the times at which they occurred.

    dXdt must accept a state and a time. E.g, this linear ODE:

    >>> def dXdt(X, t):
    ...     A = np.array([[1, -2],
    ...                   [3, -4]]) # Eigenvalues are -2 and -1, so the origin is stable.
    ...     X = np.array(X).reshape((2,1))
    ...     return np.dot(A, X)
    >>> h=.1; t0=0; tf=4; X0=(4,8)
    >>> X, T = integrate(dXdt, h, t0, tf, X0)
    >>> print X.shape, T.shape
    (2, 41) (41,)
    >>> assert T[0] == t0
    >>> assert T[-1] == tf
    >>> assert (X[:,0] == X0).all # ".all" checks that all boolean-valued
    ...                          # array elements are True
    >>> from matplotlib import pyplot as plt
    >>> f = plt.figure()
    >>> a = f.add_subplot(1, 1, 1)
```

*Do a phase portrait.*

```
>>> p = a.plot(X[0, :], X[1, :])
```

*Mark the initial condition.*

```
>>> s = a.scatter(X0[0], X0[1])
```

*Try the ODE45 "equivalent"*

```
>>> X, T = integrate(dXdt, h, t0, tf, X0, method='ode45')
```

```
>>> assert X.size > 2
```

```
"""
```

```
# Reshape the initial condition as a column vector. Allows us to accept
```

```
# row-vector numpy arrays, lists, tuples, or other list-like things.
```

```
# This might fail if X0 is something stupid, like a list-of-lists,
```

```
# or a string.
```

```
X0 = np.array(X0)
```

```
N = X0.size
```

```
X0 = X0.reshape((N,1))
```

```
# Initialize the history arrays.
```

```
# for more general, adaptive methods, we couldn't do this. At least, not
```

```
# all at once. The +h allows us to include both t0 and tf in the history.
```

```
T = np.arange(t0, tf+h, h)
```

```
X = np.empty((N, T.size))
```

```
X[:,0] = X0.ravel()
```

```
f = lambda tn, xn: dXdt(xn, tn) # symbols chosen to match Wikipedia's RK4
```

```
h = h
```

```
# some method-codes
```

```
ode45 = 'dopri5' 'ode45'
```

```
ode15s = 'vode' 'ode15s'
```

```
if method.lower() == 'rungekutta':
```

```
    for n in xrange(T.size-1):
```

```
        xn = X[:, n].reshape((N,1))
```

```
        tn = T[n]
```

```
        k1 = f(tn, xn)
```

```
        k2 = f(tn + h/2., xn + h * k1 / 2.)
```

```
        k3 = f(tn + h/2., xn + h * k2 / 2.)
```

```
        k4 = f(tn + h, xn + h * k3)
```

```
        X[:, n+1] = (xn + 1/6. * h * (k1 + 2. * k2 + 2. * k3 + k4)).ravel()
```

```

elif method.lower() == 'backwardeuler':
    for k in xrange(T.size-1): # We're using k because Wikipedia does.
        xk = X[:, k].reshape((N,1))
        tk = T[k]
        tk1 = tk + h
        xk10 = xk # initial iterate
        # While both Numpy and Scipy have fancier things available, we'll
        # deliberately use Newton-Rhapson, without putting forth the effort
        # to write our own.
        from scipy.optimize import newton
        def zeroMe(xk1):
            return xk + h * f(tk1, xk1) - xk1
        xk1 = newton(zeroMe, xk10, tol=newtontol)#, maxiter=...)
        X[:, k+1] = xk1.ravel()

elif method.lower() in ode45 + ode15s:
    # Awkward to use. scipy.integrate.odeint is easier. This code is adapted
    # from the [SciPy-User] mailing list:
    # http://mail.scipy.org/pipermail/scipy-user/2011-March/028683.html
    # It's safe to use a quite large h value for the ode15s method, since
    # the real step size is chosen automatically by SciPy. This can be
    # verified by using this method on the Naka-Rushton problem with a
    # step size larger than, say 1/6 the oscillatory period, and
    # scatter-plotting R vs t. The parts with large |dR/h|
    # automatically get smaller timesteps.
    from scipy.integrate import ode
    solver = ode(f)
    if method.lower() in ode45:
        solver.set_integrator('dopri5', nsteps=1)
        from warnings import filterwarnings
        filterwarnings("ignore", category=UserWarning)
    if method.lower() in ode15s:
        solver.set_integrator('vode', method='bdf', order=15)
    solver.set_initial_value(X0, t0)
    solver._integrator.iwork[2] = -1
    T = [t0]
    X = [X0]
    while solver.t < tf:
        solver.integrate(solver.t + h, step=True) # We should get *at least*
        T.append(solver.t) # as many steps as the other methods; perhaps
        X.append(solver.y.reshape((N,))) # more.
    T = np.array(T)
    X = np.array(X).T

```

```

else: # assume forward Euler if not ^^. Later, we might add, say,
      # Adams-Bashforth. Or perhaps backwards Euler.
    for n in xrange(T.size-1):
        xn = X[:, n].reshape((N,1))
        tn = T[n]
        X[:, n+1] = (xn + f(tn, xn) * h).ravel()

    return X, T

if __name__ == '__main__':
    '''
    The code in this block only runs if this file is invoked as a script;
    not if things from this file are imported elsewhere. Guido van Rossum
    disapproves of this usage, but it's just so handy.
    '''
    # Test that documentation examples are correct.
    import doctest
    doctest.testmod()

    # Do a pseudo-triangle-wave thing.
    def dXdt(X, t):
        X = np.array(X).reshape((2,1))
        x = X[0,0]
        y = X[1,0]
        return (np.array([np.cos(.05423*t), np.sin(t)]) +\
                np.array([np.cos(1.121235432*x), np.sin(.123*y)]).reshape((2,1))
        X, T = integrate(dXdt, h=.1, t0=0, tf=4, X0=(42, 68), method='rungekutta')
    from matplotlib import pyplot as plt
    # f = plt.figure()
    # a = f.add_subplot(1, 1, 1)
    # a.plot(X[0,:], X[1,:]) # will plot both X[0,:], and X[1,:] vs. T

    # Display any plots that may have been generated.
    # plt.show()

```