# ME-GY 6923 Simulation Tools for Robotics LECTURE 3

William Z. Peng, Ph.D.

NYU TANDON SCHOOL OF ENGINEERING

Numerical Methods, Algorithms, and Error Analysis / MATLAB - Part 2

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### Lecture Overview



#### • Last Lecture

MATLAB - Numerical Methods, Algorithms, Solvers, and Error Analysis

- Finite Difference Methods
  - Forward/Backward
  - 2-Step/Multi-step
  - Accuracy derivation for these methods

#### This lecture

We will look into some numerical methods, algorithms, and solvers (for solving differential equations)

#### Next lecture

We will begin our formal discussion of modeling using Simulink

# Numerical Solutions of ODEs (Example 3-1)



### Example of Initial Value Problem (IVP): Lotka-Volterra equation (predator-prey)

• In MATLAB, type "openExample('matlab/lotkademo')"

$$\begin{cases} R' = R - \alpha FR \\ F' = \beta RF - F \end{cases}$$

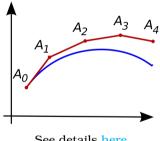
- F(t) is the number of foxes (predator) at time t
- R(t) is the number of rabbits (prey) at time t
- R' is the rate of growth of the rabbit population
  - R' increases with R but decreases with F (more foxes to eat the rabbits)
- F' is the rate of growth of the fox population
  - ullet F' decreases F (food becomes scarce) but increases with R

No analytical solution exists – problem must be solved numerically

# Euler Method - Numerical Algorithm for ODEs



- Simplest algorithm (a.k.a forward Euler Method)
- We will look at a case where n=1 (first order):  $\dot{x} = f(x(t)) \ n = 1 \rightarrow \text{one } 1^{\text{st}} \text{ order ODE (Needs 1 initial)}$ condition)
- Method valid for case n > 1:  $n>1\rightarrow n^{\rm th}$  order ODE is converted into a system of n  $1^{st}$  order ODEs. Needs n initial conditions
- Assumptions: uniform h and x has as many continuous derivatives as needed in order to analyze the accuracy of the methods using Taylor's theorem



See details here

### **Euler Method**



• One-step method: the <u>one-step forward finite difference</u> is used to approximate the time derivative of the solution at each node

# One-step forward difference

$$\dot{x}(t_k) = f(x(t_k)) \approx \frac{x(t_{k+1}) - x(t_k)}{h} \to f(x_k) = \frac{x_{k+1} - x_k}{h}$$

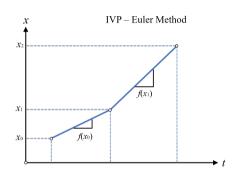
- Starting from IC  $x_0 = x(t_0)$ , the approximate solution at each time step is given by the iterative formula:  $x_{k+1} = x_k + hf(x_k)$
- Evaluating this iterative formula step by step, for all k = 0, ..., N (N + 1 = number of total mesh points), we find the numerical solution to the ODE  $\rightarrow$  Using the numerical method, the ODE is transformed into a set of algebraic equations

### Qualitative Analysis:

Steps 1-4 describe the Euler Method algorithm:

- **1** Initial conditions:  $x(t_0) = x_0$
- **2** From the D.E.:  $\dot{x} = f(x_0)$ 
  - This gives the slope at the initial time  $t_0$  and it is assumed constant for the entire h
- **3** From the previous step, the approximate solution at the next time-step  $x_1 = x_0 + f(x_0)h$  may be found
- **4** From  $x_1$ , find  $f(x_1)$ , which is the new slope, from the D.E. and keep moving forward, one step at a time

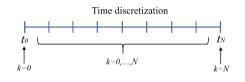
Note: Because the Euler Method is based on the one-step forward infinite difference method, it is also called a one-step method (whose error is O(h))



**D.E.**: 
$$\dot{x}(t) = f(x(t)), n = 1$$



- Consider:  $\mathbf{x}_E = [x_0, x_1, x_2, ..., x_N]$ , where  $x_0$  is known and  $x_1, x_2, ..., x_N$  are N algebraic equations
- With:  $x_{k+1} = x_k + f(x_k)h$ , where  $h = t_{k+1} t_k$  can be evaluated for k = 0, ..., N-1 (N times)



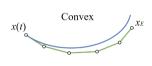
The time interval is initially discretized in N+1 nodes or N intervals

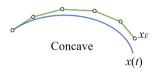
What can we say about the solution  $x_E$ ?

- It is approximated, and
- ullet It is either larger or smaller than the solution x(t) (which is not known)



For intervals of x(t) that are concave and convex:





it may be qualitatively said that:

$$x_E < x(t)$$

if in that interval, 
$$x(t)$$
 convex

$$x_E > x(t)$$

if in that interval, x(t) concave



### IVP with Euler Method and qualitative argument about accuracy

For: 
$$x' = f(t, x)$$

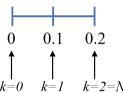
$$x' = t^2 - x^2$$

with the initial condition:  $x(0) = x_0 = 1$ 

$$x_{k+1} = x_k + h f(t_k, x_k)$$

evaluate for k = 0, 1, 2:

3-nodes (h = 0.1)



• 
$$k = 0$$
  $x_1 = x_0 + hf(0, x_0) = 1 + 0.1 \cdot (0^2 - 1^2) = 1 - 0.1 \cdot 1 = 0.9$ 

• 
$$k = 1$$
  $x_2 = x_1 + hf(t_1, x_1) = 0.9 + 0.1 \cdot (0.1^2 - 0.9^2) = 0.9 - 0.08 = 0.82$ 

• 
$$k = 2$$
  $x_3 = x_2 + hf(t_2, x_2) = 0.82 + 0.1 \cdot (0.2^2 - 0.82^2) = 0.82 - 0.0632 = 0.757$ 

# Euler Method - Example 3-2



NODE	t	x	f	hf
0	0	1	-1	-0.01
1	0.1	0.9	-0.8	-0.08
2	0.2	0.82	-0.632	-0.0632

$$\mathbf{x}_E = \left[ \begin{array}{c} 0.9 \\ 0.82 \\ 0.757 \end{array} \right]$$

- Curvature: x'' = 2t 2xx'
- At t=0,  $x_0=1$ ,  $x_0'=f_0=-1$  and  $x_0''=-2\cdot 1\cdot (-1)=2>0$ , so convex
- At t = 1,  $x_1 = 0.9$ ,  $x_1' = f_1 = -0.8$  and  $x_1'' = 0.2 2 \cdot 0.9 \cdot (-0.8) = 1.64 > 0$ , so still convex

# Euler Method - Example 3-3



For: 
$$y' = f(t, y)$$

$$y' = y$$

with the initial condition:  $y(0) = y_0 = 1$ 

$$y_{k+1} = y_k + hf(y_k)$$

we want to approximate y(4):

• 
$$k = 0$$
  $y_1 = y_0 + hf(y_0) = 1 + 1 \cdot 1 = 2$ 

• 
$$k = 1$$
  $y_2 = y_1 + hf(y_1) = 2 + 1 \cdot 2 = 4$ 

• 
$$k=2$$
  $y_3=y_2+hf(y_2)=4+1\cdot 4=8$ 

• 
$$k = 3$$
  $y_4 = y_3 + hf(y_3) = 8 + 1 \cdot 8 = 16$ 

The solution to the differential equation is:  $y(t) = e^t$ , so  $y(4) = e^4 \approx 54.598$ , while the Euler Method approximation result is 16. This is due to the very large step size

We can look at this in MATLAB and try different step sizes h



- Recall: truncation error comes from the finite difference approximation used in the current method. Recall: It is the amount by which the true solution fails to satisfy the current difference equation
- For: x' = f(t, x)
- By expanding the true solution with the Taylor's theorem:

$$x(t_{k+1}) = x(t_k) + h\dot{x}(t_k) + \frac{h^2}{2}\ddot{x}(\xi_k)$$

$$= x(t_k) + hf(t_k, x(t_k)) + \frac{h^2}{2}\ddot{x}(\xi_k) \text{ with } \xi \in [t_k, t_{k+1}]$$

which can be rewritten as:  $\frac{x(t_{k+1})-x(t_k)}{h}=f(t_k,x(t_k))+\frac{h}{2}\ddot{x}(\xi_k)$ 

- Compare with the finite difference used in Euler's method:  $\frac{x_{k+1}-x_k}{h}=f(t_k,x(t_k))$
- <u>Local</u> truncation error is  $+\frac{h^2}{2}\ddot{x}(\xi_k) \to \text{Euler's method is order } O(h^2)$  (as expected  $\to$  Forward Difference-based)



- The Euler algorithm is first order accurate. However, reducing the step size *h* comes at a price:
  - Increase the number of computation (mesh) points N
  - Increase cumulative error, due to roundoff:

$$\frac{x_{k+1}(1+\delta_1) - x_k(1+\delta_2)}{h} = \frac{x_{k+1} - x_k}{h} + \frac{x_{k+1}\delta_1 - x_k\delta_2}{h}$$

with  $|\delta_i| < \varepsilon_m$ , an upper bound for roundoff can be found:

$$\frac{x_{k+1}\delta_1 - x_k\delta_2}{h} \le \frac{|x_{k+1}| |\delta_1| + |x_k| |\delta_2|}{h} \le \frac{|x_{k+1}| \varepsilon_m + |x_k| \varepsilon_m}{h} \le \frac{\varepsilon_m \left(|x_{k+1}| + |x_k|\right)}{h} \propto \frac{\varepsilon_m}{h}$$

• As we saw before, the best trade off is when both errors are comparable: truncation  $\sim$  roundoff  $\rightarrow h \approx \frac{\varepsilon_m}{h} \rightarrow h \approx \sqrt{\varepsilon_m}$  (for Euler Method)



- Local truncation error  $O(h^2)$ : the error that is contributed at each step (it's relative to one step of the Euler algorithm)
- Global truncation error: for the entire solution we evaluate N steps (when we have N+1 nodes)  $\to$  global error  $=N\times O(h^2)\to {\rm accumulated\ error}\to =O(h)$
- $\bullet$  A method is called consistent if its local truncation error approaches 0 as  $h\to 0$  (impractical)
- Euler Method is convergent (for a well-posed problem), because it can be shown that As  $h \to 0$ , the max difference between  $x_{\rm E}$  and  $x(t) \to 0$ , for any mesh point in the fixed interval of t (we won't show this)

# Euler Method - Summary



In dynamical system simulation, the following precautions should be taken:

- Select a suitable step size: not too large nor too small
- The Forward Euler method is the simplest to implement but can become unstable and lead to inaccuracy
- Improved algorithms have been developed: Runge-Kutta, Adams, etc. These have higher order accuracy
- Because finding a suitable step size is very difficult in general, many ODE solvers support a variable step size method: when the error estimate<sup>(\*)</sup> is large, smaller step size should be chosen, while when the error estimate is small, larger step size should be selected.
  - (\*) Error estimate: Matlab solvers have a way of estimating local error (local = at every time step)

# Advanced Algorithms

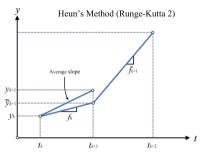


# Multi-step method: Heun's method (Improved Euler's Method or Runge Kutta $2^{\rm nd}$ order)

- Graphical procedure: y' = f(y(t))
- Method:  $y_{k+1} = y_k + h\left(\frac{f_k + \bar{f}_{k+1}}{2}\right)$  Eq. (i)
- where  $\tilde{f}_{k+1}$  is evaluated using the standard Euler Method:

$$\tilde{f}_{k+1} = f(y_{k+1}, \tilde{y}_{k+1})$$

with  $\tilde{y}_{k+1} = y_k + hf_k$  (standard Euler and intermediate step only to eliminate  $\tilde{f}_{k+1}$ )



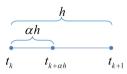
- It may be apparent that this is  $O(h^2)$ , since even though Eq. (i) looks like a 1-step method, this method is more similar to a 2-step method, given that there is an intermediate step
- By a similar reasoning, it is possible to further improve the order of accuracy as long as a new algorithm is delivered, that involves additional intermediate steps (which improve the estimate of the slope), leading to the fourth-order Runge-Kutta algorithm

# **Advanced Algorithms**



### Classic 4th order Runge-Kutta:

$$\begin{split} \tilde{y}_{k+\alpha} &= y_k + \alpha h f(t_k, x_k) \\ y_{k+1} &= y_k + \beta h f(t_k, x_k) + \gamma h f(t_k + \alpha h \tilde{y}_{k+1}) \end{split}$$



- Parameters  $\alpha, \beta, \gamma$  must be chosen to match Taylor expansion of real solution with the finite difference iterative rule
- Doing so will yield:  $y_{k+1} = y_k + h \frac{K_1 + 2K_2 + 2K_3 + K_4}{6}$  where:

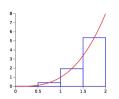
$$\begin{array}{ll} K_1 = f(t_k,y_k) & K_3 = f(t_k + \frac{h}{2},y_k + h\frac{K_2}{2}) \\ K_2 = f(t_k + \frac{h}{2},y_k + h\frac{K_1}{2}) & K_4 = f(t_k + h,y_k + hK_3) \end{array} \ \ \text{using the } O(h^4) \text{ method}$$

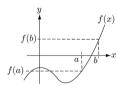
# **Advanced Algorithms**

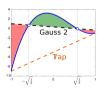


#### Other methods include:

- Midpoint Rule
- Adams-Bashforth/Adams-Moulton
- Quadrature







### MATLAB Solutions to ODEs



### Main commands and general rules of thumbs:

- ode45 is based on an explicit Runge-Kutta formula (4,5). It is a one-step solver, i.e., in computing  $x(t_{k+1})$ , it needs only the solution at the immediately preceding time point,  $x(t_k)$ . In general, is the best function to apply as a *first try* for most problems
- <u>ode23</u> is an implementation of an explicit Runge-Kutta (2,3). It may be more efficient than <u>ode45</u> at crude tolerances and with moderate stiffness
- <u>ode113</u> is a variable order Adams-Bashforth-Moulton PECE solver. It may be more efficient than ode45 at stringent tolerances and when the ODE file function is particularly expensive to evaluate. ode113 is a *multistep* solver it normally needs the solutions at several preceding time points to compute the current solution

### MATLAB Solutions to ODEs



The aforementioned algorithms are intended to solve non-stiff systems. If they appear to be unduly slow, try using:

- ode15s is a variable order solver based on the numerical differentiation formulas (NDFs) or backward differentiation formulas (BDFs, also known as Gear's method)
- Try ode 15s when ode 45 fails, or is very inefficient, and you suspect that the problem is stiff, or when solving a differential-algebraic problem

#### Resources:

https://www.mathworks.com/help/matlab/ordinary-differential-equations.html?s\_tid=srchtitle

https://www.mathworks.com/help/matlab/math/choose-an-ode-solver.html

https://blogs.mathworks.com/cleve/2014/05/26/ordinary-differential-equation-solvers-ode23-and-

### MATLAB Solutions to ODEs



The main syntax of the command:

## **Syntax**

[t,x]=ode45(Fun,tspan, $x_0$ ,options,additional parameters);

- The format is consistent for all MATLAB "ode" solvers (e.g. ode23, ode45, etc.)
- Options can be accessed with the odeget() and odeset() commands
- Fun: must contain the descriptive function/functions
- Differential equation can be described in one of the following way:
  - Anonymous functions:
     y = @(t,x,additional parameters)The function content
  - M-functions: function  $x_1$  = Fun(t,x,additional parameters)

## Control Parameters of ODEs Solvers



options	parameter description
RelTol	relative error tolerance, with a default value
	of 0.001, i.e., the relative error is $0.1\%$
	in some applications, smaller values should
	be used.
AbsTol	absolute error tolerance, with a default value
	of $10^{-6}$ .
MaxStep	maximum allowed step size.
Mass	mass matrix in differential algebraic equations
Jacobian	Jacobian matrix $\partial f/\partial x$ function name; if the
	Jacobian matrix is known, the speed of
	computation is increased.

>> f=odeget; f.RelTol=1e-8;

http://www.mathworks.com/help/matlab/ref/odeset.html http://www.mathworks.com/matlabcentral/answers/26743-absolute-and-relative-tolerance-definitions

## Stiff ODEs



- The solution of certain systems changes very rapidly over certain time intervals, while it changes slowly in other parts
- Solution to these systems require a variable step size method
- If stiffness is relevant, requires particular ode solvers (ode45 won't work)
- In case of ODE of order > 1, we have stiff systems when the solutions of each state variable have very different range and behavior. Some variables change very fast and other change very slowly

# Error Analysis



### Quantitative error analysis:

- The solution's convergence can be observed qualitatively by looking at plots obtained with different values of h (e.g. see the Euler 2 MATLAB example)
- There are several quantitative analyses that can be done:
  - 1: Compare error vector of numerical vs. analytical solution (if any)
  - 2: Compare the error vector of various numerical solutions, obtained with different methods/tolerances

# Error Analysis



### Error vector of numerical vs. analytical:

• Assume the analytical solution is known, e.g.:

$$y(t) = \frac{1}{2} + e^t \left( -\frac{3}{20}\sin(t) + \frac{1}{2}\cos(t) + \frac{3}{20}t\cos(t) + \frac{1}{4}t\sin(t) \right)$$

- Implement in MATLAB
- Evaluate the function at the same mesh points  $t_k$  obtained from the numerical solution  $[\mathbf{t}, \mathbf{y}_{\text{num}}]$  with dimension  $[N \times 1]$ . This means, substitute variable t with vector
- Calculate the 2-norm of error vector  $\mathbf{e} = \mathbf{y}(t_k) \mathbf{y}_{\text{num}}$ , with k = 1, ..., N

$$\parallel e \parallel = \sqrt{e_1^2 + e_2^2 + \dots + e_N^2}$$

### Conversion of ODE sets



• Convert the differential equation of other forms to the standard form

$$\dot{\mathbf{x}} = \mathbf{f}(t, \mathbf{x})$$

• Converting a single high-order ODE

$$y^{(n)} = f(t, y, \dot{y}, ..., y^{(n-1)})$$

• A set of state variables can be selected as:

$$x_1 = y, x_2 = \dot{y}, ..., x_n = y^{(n-1)}$$

## Conversion of ODE sets



The original high-order ODE can be converted to the following standard form:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \vdots \\ \dot{x}_n = f(t, x_1, x_2, ..., x_n) \end{cases}$$

$$\begin{cases} x_1(0) = y(0) \\ x_2(0) = \dot{y}(0) \\ \vdots \\ x_n(0) = y^{(n-1)}(0) \end{cases}$$

# Converting High-Order ODE sets



The ODE set:

$$\begin{cases} x^{(m)} = f(t, x, \dot{x}, ..., x^{(m-1)}, y, ..., y^{(n-1)}) \\ y^{(n)} = g(t, x, \dot{x}, ..., x^{(m-1)}, y, ..., y^{(n-1)}) \end{cases}$$

Select the state variables:

$$\begin{cases} x_1 = x \\ \vdots \\ x_m = x^{(m-1)} \\ x_{m+1} = y \\ \vdots \\ x_{m+n} = y^{(n-1)} \end{cases}$$

$$\begin{cases} \dot{x}_1 = x_2 \\ \vdots \\ \dot{x}_m = f(t, x_1, x_2, ..., x_{m+n}) \\ \dot{x}_{m+1} = x_{m+2} \\ \vdots \\ \dot{x}_{m+n} = g(t, x_1, x_2, ..., x_{m+n}) \end{cases}$$

### Solutions to DAEs



 In certain differential equations, some of the state variables satisfy certain algebraic constraints

$$\mathbf{M}(t, \mathbf{x})\dot{\mathbf{x}} = \mathbf{f}(t, \mathbf{x})$$

- Mass Matrix in general non-singular
- Set the Mass options. Mass = M

Example (see Exercise 4-4, below):

$$\begin{cases} \dot{x}_1 = -0.2x_1 + x_2x_3 + 0.3x_1x_2 \\ \dot{x}_2 = 2x_1x_2 - 5x_2x_3 - 2x_2^2 \\ x_1 + x_2 + x_3 - 1 = 0 \end{cases}$$

with some initial conditions



### M-function vs. Anonymous function:

Mathematical functions can be described in MATLAB in one of the following ways: M-function vs. Anonymous function (Example 1)

$$\dot{y}_1 = y_2 y_3$$
  $\dot{y}_2 = -y_1 y_3$   $\dot{y}_3 = -0.51 y_1 y_2$ 

with initial values  $y_1 = 0, y_2 = 1, y_3 = 1$ , and total time duration t = [0, 12]

# Write a script "Exercise3\_1.m"\*:

- Follows Example 1 in MATLAB ode45 documentation
- Use ODE 45
- Set tolerance
- Validate results
- Plot step size

\* Reminder: Matlab will not run a file that contains a "-" in the filename, so use a "-" instead

# MATLAB Exercise 3-2



#### Van der Pol:

Van der Pol second order non linear differential equations:

$$\ddot{y} + \mu(y^2 - 1)\dot{y} + y = 0$$

Convert to standard form:

$$\mathbf{x} = [x_1, x_2] = [y, \dot{y}] \to \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ -\mu(x_1^2 - 1)x_2 - x_1 \end{bmatrix}$$

with initial values  $x_0 = [-0.2, -0.7]$  and total time duration 20s

# Write a script "Exercise3\_2.m":

- Use ode45, with parameter  $\mu$
- Try different implementation of ODE descriptive function (anonymous and M-function)
- Visualize time responses and solution in the state space
- Stiff problem  $\rightarrow$  see when ode45 fails



### Apollo satellite:

Satisfies the following ODE:

$$\begin{cases} \ddot{x} = 2\dot{y} + x - \frac{\mu^*(x+\mu)}{r_1^3} - \frac{\mu(x-\mu^*)}{r_2^3} \\ \ddot{y} = -2\dot{x} + y - \frac{\mu^*y}{r_1^3} - \frac{\mu y}{r_2^3} \end{cases}$$

$$\mu = 1/82.45 \quad \mu^* = 1 - \mu$$

$$r_1 = \sqrt{(x_1 + \mu)^2 + x_3^2} \quad r_2 = \sqrt{(x_1 + \mu^*)^2 + x_3^2}$$

$$x(0) = 1.2, \quad \dot{x}(0) = 0, \quad y(0) = 0, \quad \dot{y}(0) = -1.04935751$$

Select the state variables:  $x_1 = x$ ,  $x_2 = \dot{x}$ ,  $x_3 = y$ ,  $x_4 = \dot{y}$ 



#### Apollo satellite:



#### DAEs:

$$\begin{cases} \dot{x}_1 = -0.2x_1 + x_2x_3 + 0.3x_1x_2 \\ \dot{x}_2 = 2x_1x_2 - 5x_2x_3 - 2x_2^2 \\ x_1 + x_2 + x_3 - 1 = 0 \end{cases}$$

The standard form of a DAE:

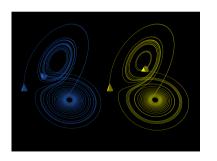
$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -0.2x_1 + x_2x_3 + 0.3x_1x_2 \\ 2x_1x_2 - 5x_2x_3 - 2x_2^2 \\ x_1 + x_2 + x_3 - 1 \end{bmatrix}$$

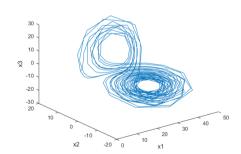
#### MATLAB commands



#### Lorenz Attractor:

$$\begin{cases} \dot{x}_1 = 8x_1(t)/3 + x_2(t)x_3(t) \\ \dot{x}_2 = -10x_2(t) + 10x_3(t) \\ \dot{x}_3 = -x_1(t)x_2(t) + 28x_2(t) - x_3(t) \end{cases}$$





# Homework and References



# Assignment

- Study Examples 3-1 3-3 and Exercises 3-1 3-5 (no need to submit)
- Complete the Simulink Onramp Course https://www.mathworks.com/learn/tutorials/simulink-onramp.html
- Upload Completion Report Certificate (as a pdf) and the Link: Once you have completed the course, select "View/Share Certificate" on the "My Self-Paced Courses" section of the Mathworks website, and post the "shareable link" to your Progress Report to Brightspace (ensure that the link works)

#### References

• Xue & Chen Chapter 3: 3.4.1 – 3.4.5