

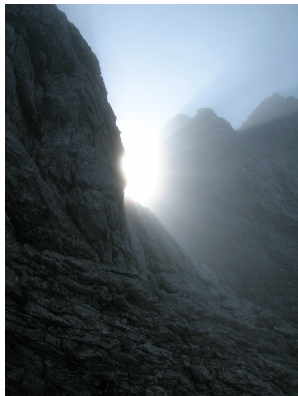
# Numerical Algorithms (COMP 3371)

Session VII: Truncation errors, stability and consistency

Dr. Weinzierl

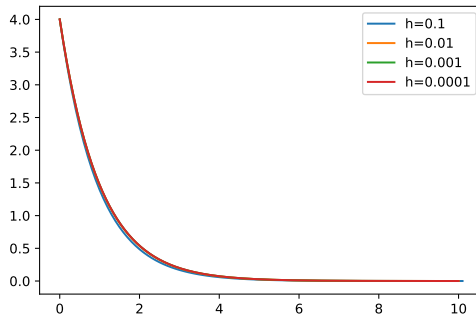
Michaelmas term 2019

- ▶ Can you explain the idea of explicit Euler at hands of a Taylor series?
- ▶ Is the explicit Euler stable w.r.t. rounding errors?
- ▶ What is the definition of machine precision?
- ▶ What is the difference between the local round-off error and the global round-off error?



Consistency  
Stability  
Consistency and convergence

# Playing around with explicit Euler



# Consistency of explicit Euler (1/2)

$$y'(t) = F(y, t)$$

- ▶ The smaller  $h$ , the better our scheme approximates the real solution
- ▶ Intuitively clear, as we used Taylor and did truncate it
- ▶ Can we show it?

# Consistency of explicit Euler (1/2)

$$y'(t) = F(y, t)$$

- ▶ The smaller  $h$ , the better our scheme approximates the real solution
- ▶ Intuitively clear, as we used Taylor and did truncate it
- ▶ Can we show it?
- ▶ Exact solution:

$$y(t + \Delta t) = \sum_{i=0}^{\infty} \frac{\Delta t^i}{i!} y^{(i)}(t)$$

- ▶ Our approximation:

$$y_h(t + \Delta t) = y_h(t) + \underbrace{\Delta t \cdot y'_h(t)}_{\text{plug } F \text{ into}} + \underbrace{\sum_{i=2}^{\infty} \frac{\Delta t^i}{i!} y^{(i)}(t)}_{\text{cut off / truncate}}$$

- ▶ Subscript  $h$  used as  $h = \Delta t$  very often denotes discretisation of continuum (time)

## Consistency of explicit Euler (2/2)

- Error equals truncated terms:

$$y_h(t + \Delta t) - y(t + \Delta t) = - \sum_{i=2}^{\infty} \frac{\Delta t^i}{i!} y^{(i)}(t)$$

- Reiterate definition:

**Consistency:** A scheme is consistent if

$$\lim_{h \rightarrow 0} y_h(t) = y(t)$$

and  $y(t)$  is the analytical solution.

- Study error for  $\Delta t \mapsto 0$  (from the right side):

$$\lim_{\Delta t \mapsto 0^+} y_h(t + \Delta t) - y(t + \Delta t) = \lim_{\Delta t \mapsto 0^+} - \sum_{i=2}^{\infty} \frac{\Delta t^i}{i!} y^{(i)}(t)$$

- Trivially goes to zero as long as derivatives are well-behaved

$$y'(t) = F(y, t)$$

**Consistency:** A scheme is consistent if

$$\lim_{h \rightarrow 0} y_h(t) = y(t)$$

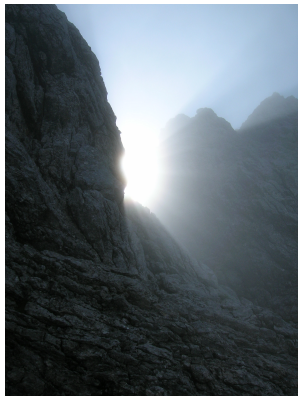
and  $y(t)$  is the analytical solution.

- ▶ Explicit Euler is trivially consistent, as we simply cut the Taylor at  $\mathcal{O}(h^2)$
- ▶ Consistency means we solve the *right* problem (in the limit)
- ▶ The  $\mathcal{O}(h^2)$  is the *truncation error*
- ▶ Consistent scheme = truncation error goes to zero with  $h \mapsto 0$

We now switch from  $\Delta t$  to  $h$  forth and back!



- ▶ Content
  - ▶ Introduce term consistency
  - ▶ Define truncation error
- ▶ Expected learning outcomes
  - ▶ The student *knows* definition of introduced terms
  - ▶ The student can *explain* what consistency means (“solve right problem”)



Consistency  
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- ▶ We know that the round-off error does not make our algorithm explode  
(if  $F$  is well-behaved)
  - ▶ We know that our system is consistent, i.e. solved (in the limit) the right problem
- ⇒ what could possibly go wrong?

# Explicit Euler with error measurements

for the test equation

**Explicit Euler:** For the test equation, we know the analytical solution and thus can directly compute the error. This does not work for more complex problems.

$$\begin{aligned}y'(t) &= \lambda y(t) \quad \text{with } y(t=0) = y_0 \\y_h(t+h) &= y_h(t) + h \cdot y_h'(t) = y_h(t) + h\lambda y_h(t) = (1 + h\lambda)y_h(t) \\y(t) &= y_0 \cdot e^{\lambda t}\end{aligned}$$

```
const double y0 = 4.0;

double t      = 0.0;
double y      = y0;
double lambda = -1.0;
double h      = 0.001;

while (t < 2.0) {                                // simulate until t=2.0
    t = t + h;
    y = (1.0+lambda*h) * y;
    double error = y - y0 * exp(lambda * t);
    std::cout << "t=" << t << ",y=" << y << ",e=" << error << std::endl;
}
```

## Writing down the (pseudo-) code

**Results for  $\lambda = -1.0$ :**

- ▶  $h=0.001$ :  $t=2.001, y=0.540259, e=-0.000541161$
- ▶  $h=0.002$ :  $t=2, y=0.540258, e=-0.00108304$
- ▶  $h=0.004$ :  $t=2, y=0.539174, e=-0.00216681$
- ▶  $h=0.032$ :  $t=2.016, y=0.515475, e=-0.0172737$
- ▶  $h=0.256$ :  $t=2.048, y=0.375529, e=-0.140442$

⇒ Please validate yourself (bottom-up)!

**Observations:**

- ▶ Some round-off error in  $t$  for  $h=0.001$
  - ▶ Halving  $h$  roughly reduces error by factor of two, i.e.
  - ▶ error decreases if we reduce  $h$  (consistency)
  - ▶ Every run here gives us some meaningful result (subject to errors)
- ⇒ Confirms our assumption that everything is fine

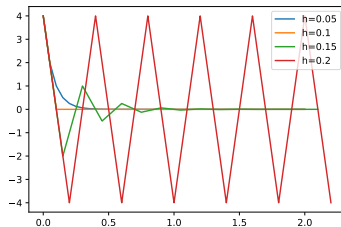
## Another “material” parameter

With  $\lambda = -10.0$ :

- ▶  $dt=0.001$ :  $h=2.001, y=7.38048e-09, e=-7.82103e-10$
- ▶  $h=0.002$ :  $t=2, y=6.73187e-09, e=-1.51275e-09$
- ▶  $h=0.256$ :

```
t=0.256,y=-6.24,e=-6.54922
t=0.512,y=9.7344,e=9.7105
t=0.768,y=-15.1857,e=-15.1875
t=1.024,y=23.6896,e=23.6895
t=1.28,y=-36.9558,e=-36.9558
t=1.536,y=57.6511,e=57.6511
t=1.792,y=-89.9357,e=-89.9357
t=2.048,y=140.3,e=140.3
```

# Overshooting of explicit Euler



- ▶ Stability typically is studied at hands of Dahlquist test equation  $\partial_t y = \lambda y$  with fixed time step size  $\Delta t = h$
- ▶ We know analytical solution, and can construct stable and unstable solutions due to the choice of  $\lambda$
- ▶ Explicit Euler (on step):

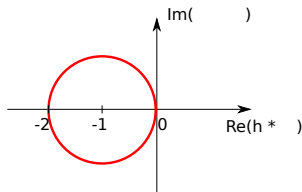
$$y_h(nh) = (1 + h\lambda)y_h((n-1)h)$$

- ▶ Apply recursion/induction to derive global scheme for test equation
- ▶ Global scheme:

$$y_h(nh) = (1 + h\lambda)^n y_h(0)$$

- ⇒ We can now determine the  $n$ th approximation directly without any recursion.
- ⇒ We know for  $\lambda < 0$  that it should go towards 0 (attractive/stable critical point).
- ⇒ Does it do so?





$$y_h(nh) = (1 + h\lambda)^n y_h(0)$$

$$\lim_{n \rightarrow \infty} y_h(nh) = 0 \quad \Leftrightarrow \quad |1 + h\lambda| < 1$$

- ▶ We see stability for  $|1 + h\lambda| < 1$ ,  
i.e.  $0 < h < -2/\lambda$   
 $\Rightarrow$  consistency is trivial but stability not
- ▶ We now have a formal criterion for  
oscillations of error in the test equation
- ▶ For another ODE, we have to redo  
these steps

Round-off stability: . . . (covered that one)

Zero stability: Small perturbations of input data do not make the truncation error explode as  $h \mapsto 0$ .

- ▶ Clear/trivial for explicit Euler
- ▶ Necessary for a consistent scheme
- ▶ Kind of generic for explicit Euler

Absolute (A) stability: Small perturbations of input data do not make the truncation error explode.

- ▶ For every  $\lambda$ , we can construct  $h$  such that explicit Euler breaks
- ▶ Necessary for a consistent scheme
- ▶ Depends on problem

- ▶ Content
  - ▶ Discuss when explicit Euler fails and how
  - ▶ Write down global iteration scheme
  - ▶ Derive stability criteria
  - ▶ Sketch proper time step choice for explicit Euler
- ▶ Expected learning outcomes
  - ▶ Student knows formalisation of convergence analysis
  - ▶ Student can explain formally and at hands of sketches why and where explicit Euler becomes unstable
  - ▶ Student can analyse any time stepping scheme w.r.t. stability
- ▶ Revision for exam
  - ▶ Experiment with different time step sizes for the two-body problem from the coursework (collision)



Consistency  
Stability  
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**Lax Equivalence Theorem:** An algorithm converges iff it is consistent and stable.

- ▶ These are the schemes we are searching for
- ▶ We can “rely” our computer simulation’s outcome

$$y' = F(t, y)$$

**Local error:** The local error is the error we make in one step.

- Taylor series:  $y(t + h) = y(t) + hy'(t, y) + h^2/2y''(t, y) + h^3/6y'''(t, y) + \dots$
- Explicit Euler:  $y_h(t + h) = y_h(t) + hy'(t, y_h(t))$
- Error:  $e(t) = y_h(t) - y(t)$

**First time step:**

$$e(h) = y_h(h) - y(h)$$

$$y' = F(t, y)$$

**Local error:** The local error is the error we make in one step.

- ▶ Taylor series:  $y(t + h) = y(t) + hy'(t, y) + h^2/2y''(t, y) + h^3/6y'''(t, y) + \dots$
- ▶ Explicit Euler:  $y_h(t + h) = y_h(t) + hy'(t, y_h(t))$
- ▶ Error:  $e(t) = y_h(t) - y(t)$

**First time step:**

$$\begin{aligned} e(h) &= y_h(h) - y(h) \\ &= \underbrace{y_h(0) - y(0)}_{=0} + h \cdot \underbrace{F(0, y_h(0)) - F(0, y(0))}_{=0} + \dots \end{aligned}$$

- ▶ Error is  $h \cdot (f'(t, y) - f'(t, y_h(t))) + \mathcal{O}(h^2) = \mathcal{O}(h^2)$  as the  $y'$  are exact as well.
- ▶ Scheme is second order.

**Global error:** The global error is the error between the numerical solution and the true solution (with multiple local steps in-between) at a given point.

⇒ Is the global error just the sum of all the local errors?

## First time step:

- ▶ Error is  $h \cdot (y'(t, y) - y'(t, y_h(t))) + \mathcal{O}(h^2) = \mathcal{O}(h^2)$  as  $y'_h$  is exact.
- ▶ Scheme is second order.

## Second time step:

- ▶ There is an additional error that is propagated.
- ▶ It results from the fact that  $y'(t, y) - y'(t, y_h(t)) \neq 0$ .
- ▶ This reduces the scheme to first order, i.e. the inaccurate derivatives pollute the solution.



**Convergence order  $p$ :** An algorithm converges with order  $p$  if

$$|y_h(t) - y(t)| \leq C \cdot h^p.$$

- Global property (not only single time step)
- $p = 1$  for explicit Euler (as we do not write  $t = h$ )

**Convergence (rephrased):** An algorithm converges if

$$\forall t : \lim_{h \rightarrow 0} \|y_h(t) - y(t)\| = 0.$$

Remark: We “only” need zero-stability though in practice A-stability might be more important.

Nice. But the motivation behind the whole course is that we don't know the answer and thus can't compute  $e$ !

- Error for one  $h$ :

$$e_h(t) = (y_h - y)(t)$$

Let's drop the  $t$  parameter. We always measure things at one point in time

- Error for more accurate simulation:

$$e_{h/2} = y_{h/2} - y$$

- Plug into each other:

$$e_h - e_{h/2} = y_h - h - y_{h/2} + y = y_h - y_{h/2}$$

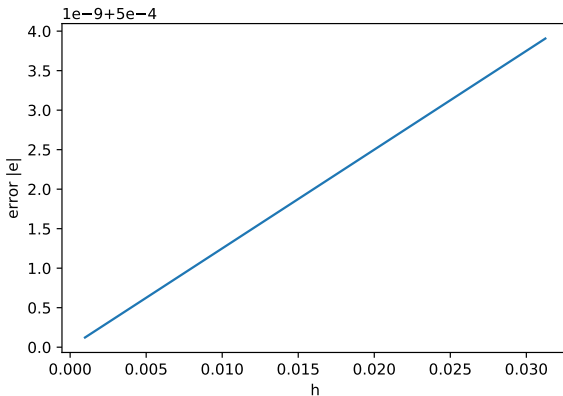
- We still do not know the error, but we know how the error has changed:

$$e \in \mathcal{O}(h^p) \Leftrightarrow e = Ce^p$$

$$e_h - e_{h/2} = \underbrace{y_h - y_{h/2}}_{\text{measure}} = Ch^p - C(h/2)^p = C(1 - \frac{1}{2^p})h^p$$

- Now continue with  $y_h - y_{h/4}$ , and  $y_h - y_{h/8}$ , and ...

# Example



- ▶ Content
  - ▶ Define convergence
  - ▶ Study local and global error
  - ▶ Convergence order
  - ▶ Discuss measurements
- ▶ Expected learning outcomes
  - ▶ The student *knows* definition of introduced terms
  - ▶ The student can *compute* convergence order for model problems
  - ▶ The student can *experimentally determine* convergence orders
- ▶ Revision for exam
  - ▶ Run some numerical experiments (for test equation and with coursework, e.g.) and determine convergence order; this also works for other pieces of coursework

# Summary, outlook & homework

## Concepts discussed:

- ▶ We have done all of our explicit Euler homework

## Next:

- ▶ We study ways how to choose proper time step sizes
- ▶ We continue our search for a better scheme which is more stable all the time
- ▶ We start to construct more accurate schemes

## Preparation:

- ▶ Solve the problem **Stiff problems** from the worksheet