# MA5233 Computational Mathematics

Lecture 17: Implicit Runge-Kutta Methods

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#### Implicit Runge-Kutta methods

Variation on the explicit Runge-Kutta methods introduced in Lecture 16.

The following example introduces a model problem where explicit methods perform poorly.

#### Example

Consider the ODE

$$y(0) = 1,$$
  $\dot{y}(t) = -y(t)$  for  $t \ge 0$ .

Solution is given by  $y(t) = \exp(-t)$ .

Numerical observations: (see example() in the accompanying Julia file)

- ▶ Midpoint method diverges if the ratio  $\frac{T}{m}$  becomes too large.
- Same holds true for Euler method.

#### Stability analysis

For the simple ODE  $\dot{y}=-y$ , we can compute explicit formulae for a single Euler / midpoint step.

► Euler: 
$$\tilde{y}(\frac{T}{m}) = y(0) + f(y(0)) \frac{T}{m} = y(0) - y(0) \frac{T}{m}$$
  
=  $(1 - \frac{T}{m}) y(0)$ .

Midpoint: 
$$\tilde{y}(\frac{T}{m}) = y(0) + f\left(y(0) + f\left(y(0)\right) \frac{T}{2m}\right) \frac{T}{m}$$
$$= y(0) - \left(y(0) - y(0) \frac{T}{2m}\right) \frac{T}{m}$$
$$= \left(1 - \frac{T}{m} + \frac{T^2}{2m^2}\right) y(0).$$

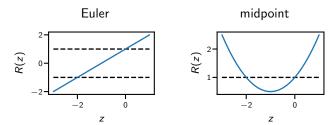
Observation: numerical solution after k steps is given by

$$\tilde{y}(\frac{T}{m}k) = R(-\frac{T}{m})^k y(0)$$
 where  $R(z) = \begin{cases} 1+z & \text{(Euler)}, \\ 1+z+\frac{z^2}{2} & \text{(midpoint)}. \end{cases}$ 

Hence,  $\lim_{k\to\infty} \tilde{y}(\frac{T}{m}k) = 0$  if and only if  $|R(-\frac{T}{m})| < 1$ .

#### Stability analysis (continued)

Plot of stability functions R(z):



Conclusion:  $\tilde{y}(\frac{T}{m}k) = R(-\frac{T}{m})^k y(0) \to 0$  if and only if  $\frac{T}{m} < 2$ . This is precisely what we observed experimentally.

#### Discussion

In previous lecture, we have seen the estimate  $|\tilde{y}(T) - y(T)| = \mathcal{O}(m^{-p})$  with p = 1 (Euler) and p = 2 (midpoint).

This is an asymptotic estimate for the limit  $m \to \infty$ .

The above stability analysis sheds some light on the behaviour of Runge-Kutta methods in the preasymptotic regime  $m \ll \infty$ .

See also convergence() in accompanying Julia file.

#### Linearisation of ODEs

Discussion so far was specific to the ODE  $\dot{y}=-y$ , but the conclusions are relevant for generic ODEs  $\dot{y}=f(y)$  as long as there is an *attractive fixed-point*, i.e. a  $y_f$  such that  $f(y_f)=0$  and  $\nabla f(y_f)$  has at least one eigenvalue  $\lambda$  with  $\text{Re}(\lambda)<0$ .

"Proof". For y close to  $y_f$ , we obtain

$$\frac{d}{dt}(y(t) - y_f) = f(y(t)) 
= f(y_f) + \nabla f(y_f) (y(t) - y_f) + \mathcal{O}(||y(t) - y_f||^2) 
= \nabla f(y_f) (y - y_f) + \mathcal{O}(||y(t) - y_f||^2).$$

Assume  $\nabla f(y_f)$  has eigendecomposition  $\nabla f(y_f) = V \Lambda V^{-1}$ . Ignoring the  $\mathcal{O}$ -term and introducing  $y(t) - y_f = V w(t)$ , we obtain

$$V\dot{w}(t) = \frac{d}{dt}Vw(t) = \nabla f(y_f)Vw(t) = V\Lambda w(t) \iff \dot{w} = \Lambda w.$$

"Proof" (continued).

Solution to  $\dot{w} = \Lambda w$  is given by  $w_i(t) = \exp(\lambda_i t) w_i(0)$ .

We observe  $\lim_{t\to\infty} w_i(t) = 0$  if  $Re(\lambda_i) < 0$ .

Repeating the above stability analysis, one can show

$$\tilde{w}_i(\frac{T}{m}k) = R(\lambda_i \frac{T}{m})^k w_i(0)$$
 where  $R(z) = \begin{cases} 1+z & \text{(Euler)}, \\ 1+z+\frac{z^2}{2} & \text{(midpoint)}. \end{cases}$ 

Same conclusion as before:

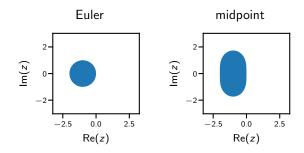
$$\lim_{k\to\infty} \tilde{w}_i(\frac{T}{m}k) = 0 \text{ if and only if } |R(\lambda_i \frac{T}{m})| < 1.$$

However, unlike before we are now also interested in the behaviour of R(z) for complex z if  $\lambda_i$  is complex.

In particular, we are interested in the stability domain

$$\big\{z\in\mathbb{C}\mid |R(z)|<1\big\}.$$

### Stability domains $\{z \in \mathbb{C} \mid |R(z)| < 1\}$



#### Example

Consider the ODE  $\ddot{x} = -x$ , or equivalently

$$\dot{y} = \begin{pmatrix} \dot{y}_1 \\ \dot{y}_2 \end{pmatrix} = \begin{pmatrix} y_2 \\ -y_1 \end{pmatrix} = f(y)$$
 with  $\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} x \\ \dot{x} \end{pmatrix}$ .

We have 
$$\nabla f = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$$
 with eigenvalues  $\lambda = \pm \iota$ .

Knowledge of the eigenvalues can be used to predict rate of divergence of Euler and midpoint methods. See harmonic\_oscillator().

### Stability functions of explicit Runge-Kutta methods

Consider Runge-Kutta scheme with Butcher tableau  $\left(\begin{array}{c|c} x & V \\ \hline & w^T \end{array}\right)$  applied to the ODE  $\dot{y} = \lambda y$ .

Solution after a single step from 0 to t is given by

$$\tilde{y}(t) = y(0) + w^T \mathbf{f} t, \quad \mathbf{f} = \lambda \left( y(0) + V \mathbf{f} t \right).$$

Simplifying these formulae yields (1 denotes vector of all-ones)

$$\tilde{y}(t) = (1 + \lambda t w^T (I - \lambda t V) \mathbf{1}) y(0).$$

Hence, stability function is given by

$$R(z) = 1 + z w^{T} (I - z V)^{-1} \mathbf{1}.$$

#### Example: midpoint method

Butcher tableau:

$$\begin{pmatrix}
0 & \\
\frac{1}{2} & \frac{1}{2} \\
\hline
 & 0 & 1
\end{pmatrix}$$

Stability function:

$$R(z) = 1 + z \begin{pmatrix} 0 & 1 \end{pmatrix} \begin{pmatrix} I - z \begin{pmatrix} 0 & 0 \\ \frac{1}{2} & 0 \end{pmatrix} \end{pmatrix}^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$
$$= 1 + z \begin{pmatrix} 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ -\frac{z}{2} & 1 \end{pmatrix}^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$
$$= 1 + z \begin{pmatrix} 1 + \frac{z}{2} \end{pmatrix}$$
$$= 1 + z + \frac{z^{2}}{2}.$$

### Stability function (recap)

$$R(z) = 1 + z w^{T} (I - z V)^{-1} \mathbf{1}$$

#### Stability domains of explicit Runge-Kutta methods

- ► For explicit methods, *V* is strictly lower triangular.
- ▶ One can show: V strictly lower triangular  $\implies R(z)$  is a polynomial.
- ▶  $\lim_{|z|\to\infty} |R(z)| = \infty$  for all polynomials R(z).
- ► Hence stability domain is bounded.

Conclusion: for all explicit methods, there is a stability constraint  $\frac{T}{m} < \Delta t_{\max}(f)$  on the time step  $\frac{T}{m}$ .

#### Discussion

It depends on application whether time-step constraint is a problem.

Next slide provides a typical example of when time-step constraints are indeed a problem.

#### Example: separation of time scales

$$\begin{pmatrix} \dot{y}_1 \\ \dot{y}_2 \end{pmatrix} = \begin{pmatrix} 1000\iota \ y_1 \\ 1 \end{pmatrix}, \qquad \begin{pmatrix} y_1(0) \\ y_2(0) \end{pmatrix} = \begin{pmatrix} 0.001 \\ 0 \end{pmatrix}.$$

Behaviour of solution:

- $ightharpoonup y_1(t) = 0.001 e^{1000\iota t}$ : high-freq. oscillation with small amplitude.
- $ightharpoonup y_2(t) = t$ : linear motion.

Why time-step constraint is problematic:

- $\triangleright$  Oscillations in  $y_1$  dictate largest admissible time step but contribute very little to final solution due to small amplitude.
- ▶ We would be happy not to resolve the oscillations of  $y_1$  as long as doing so does not affect the linear motion in  $y_2$ .
- In explicit methods, this is not possible: choosing a time-step much larger than the oscillation period  $\frac{2\pi}{1000}$  will result in exponential blow-up in  $\tilde{y}_1$ .

### **Example (continued)**

A situation as described on previous slide frequently arises in molecular dynamics simulations (https://youtu.be/GClPr5Qpd5A).

Consider a two-atom molecule (e.g. oxygen  $O_2$ ):



- Bond between the atoms introduces a high-frequency oscillation within the molecule.
- ▶ Centre of mass moves very slow compared to this oscillation.
- ► Step size is determined by oscillation frequency even though we mostly care about translation and rotation of molecule.
- Common approach to avoid step-size constraint: replace stretchable with rigid bond.

#### Remark

We will encounter another example of "separation of time-scales" when we discuss numerical methods for parabolic PDEs.

Stability function (recap): 
$$R(z) = 1 + z w^T (I - z V)^{-1} \mathbf{1}$$

### Implicit Runge-Kutta methods

Stability constraints can be avoided if we allow nonzeros in the upper triangle of V, since then R(z) becomes a rational function which may be bounded for  $|z| \to \infty$ .

#### **Examples**

▶ Implicit Euler method:  $\tilde{y}(t) = y(0) + f(\tilde{y}(t)) t$ .

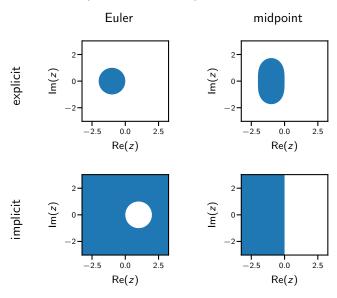
$$\left(\begin{array}{c|c} 1 & 1 \\ \hline & 1 \end{array}\right), \qquad R(z) = 1 + \frac{z}{1-z} = \frac{1}{1-z}.$$

► Implicit midpoint method:

$$\tilde{y}(t) = y(0) + f\left(\tilde{y}\left(\frac{t}{2}\right)\right)t, \qquad \tilde{y}\left(\frac{t}{2}\right) = y(0) + f\left(\tilde{y}\left(\frac{t}{2}\right)\right)\frac{t}{2}.$$

$$\left(\frac{\frac{1}{2} \left|\frac{1}{2}\right|}{1}\right), \qquad R(z) = 1 + \frac{z}{1 - \frac{z}{2}} = \frac{2 + z}{2 - z}.$$

**Stability domains**  $\{z \in \mathbb{C} \mid |R(z)| < 1\}$ 



#### Discussion: explicit vs. implicit methods

Main drawback of implicit methods:

must solve equations of the form y = F(y).

Not much of a problem if F(y) is linear and fast solvers are available. If not, solving y = F(y) may be as expensive as taking many small explicit time-steps.

Conclusion: which algorithm is best is highly problem-specific.

#### Remark

y = F(y) may be a non-linear equation!

Time permitting, we will discuss algorithms for solving such problems later in this module.

#### Discussion: Euler vs s-stage Runge-Kutta

Error  $e_m$  of Runge-Kutta methods converges as  $e_m = \mathcal{O}(m^{-p})$  for some p > 1 compared to  $e_m - \mathcal{O}(m^{-1})$  for Euler.

However, this faster convergence comes at the price of more computations per step.

Can we design methods which are as cheap as Euler and as fast as RK?

#### Observation

RK methods sample f(y) at a number of points  $y \in [y(0), y(t)]$  to learn about higher-order derivatives of f and then use this knowledge to predict y(t).

However, for all time steps  $t_k$  other than the first, we already have samples  $f(\tilde{y}(t_k))$ .

Multistep methods use these samples to predict  $\tilde{y}(t_{k+1})$ . More details on next slide.

#### **Terminology**

Runge-Kutta methods are also called *single-step methods* because they only look at a single "step"  $y_k := y(t_k)$  to predict  $y_{k+1}$ . Multistep methods are called multi-step because they look at several steps  $y_{k-n}, \ldots, y_k$  to predict  $y_{k+1}$ .

### Explicit multistep methods (Adams-Bashford)

$$\tilde{y}_{k+1} = \tilde{y}_k + \Delta t \left( c_0 f(\tilde{y}_k) + \ldots + c_n f(\tilde{y}_{k-n}) \right).$$

### Implicit multistep methods (Adams-Multon)

$$\tilde{\mathbf{y}}_{k+1} = \tilde{\mathbf{y}}_k + \Delta t \left( c_{-1} f(\tilde{\mathbf{y}}_{k+1}) + c_0 f(\tilde{\mathbf{y}}_k) + \ldots + c_n f(\tilde{\mathbf{y}}_{k-n}) \right).$$

#### Discussion

- ► Theory of multistep methods is similar to theory for RK methods.
- Multistep methods are useful if evaluation of f(y) is expensive. However, even in that case they are at most a constant factor faster than Runge-Kutta methods.
- ▶ Multistep methods require another method to compute  $\tilde{y}_1, \dots, \tilde{y}_n$ .

#### References and further reading

- DifferentialEquations.jl (http://docs.juliadiffeq.org/) Very powerful library of ODE solvers. Looking through the documentation gives a good idea of what people use in practice.
  - Off-topic, but fascinating: http://tutorials.juliadiffeq.org/html/type\_handling/02-uncertainties.html
- ► E. Suli and D. F. Mayers. *An Introduction to Numerical Analysis*. Cambridge University Press (2003), doi:10.1017/CB09780511801181
  - Can be accessed online for free via the library website!