Guranteed numerical integration based on explicit methods of Runge-Kutta

Alexandre Chapoutot

U2IS, ENSTA ParisTech

May 14, 2014



Context



- 2 Numerical solution of IVP
- 3 Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

Scientific context

Fact: Simulink is a *de facto* standard in industry for model-based design of control-command systems because:

• it can model and numerically simulate hybrid systems, i.e. it mixes ordinary differential equations (ODE) and (very generally) state transition systems.

Goal

Defining and applying formal verification methods on Simulink models.

Main challenges

- Solve ODEs for sets of initial values and bounded parameters.
- Handle interactions between continuous-time and discrete-time components.

Numerical solution of IVP



- 2 Numerical solution of IVP
- 3 Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

Goal of numerical integration

Recall, we consider IVP (initial value problem):

$$\dot{\mathbf{x}} = f(t, \mathbf{x})$$
 with $x(0) = \mathbf{x}_0$. (1)

This problem (Cauchy problem) admits a unique solution $x(t; \mathbf{x}_0)$ on \mathbb{R} , if $f : \mathbb{R} \times \mathbb{R}^n \times \mathbb{R}^n$ is continuous in t and Lipschitz in \mathbf{x} that is:

$$\forall t, \forall \mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^n, \exists L > 0, \quad \parallel f(t, \mathbf{x}_1) - f(t, \mathbf{x}_2) \parallel \leq L \parallel \mathbf{x}_1 - \mathbf{x}_2 \parallel$$

Goal

- Compute a sequence of time instants $t_0 \leq t_1 \leq \cdots \leq t_n$
- Compute a sequence of values $\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_n$ such that

$$orall i \in [0, n], \quad x_i pprox x_i(t_i; \mathbf{x}_0)$$
 .

Remark:

$$\dot{\mathbf{x}} = f(t, \mathbf{x}) \Leftrightarrow \dot{\mathbf{z}} = \begin{pmatrix} \dot{\mathbf{x}} \\ \dot{t} \end{pmatrix} = \begin{pmatrix} f(t, \mathbf{x}) \\ 1 \end{pmatrix} = g(\mathbf{z})$$

Example of numerical integration method: Euler's method

Consider a simple IVP:

$$\dot{x}=-rac{x^3}{2}$$
 with $x(0)=1$.

The exact solution is $x(t) = \frac{1}{\sqrt{1+t}}$.

We consider two fixed-step methods (Euler and Heun) that is they compute the sequence of time instants such that $t_{i+1} = t_i + h$.

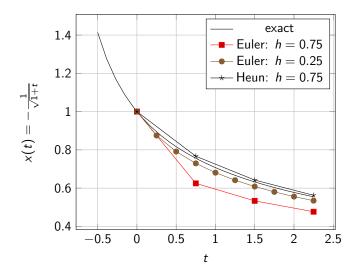
• The Euler's method computes the sequence of values

$$x_{i+1} = x_i + h \times -\frac{x_i^3}{2}$$

• The Heun's method computes the sequence of values:

$$k_1 = x_i + h \times -\frac{x_i^3}{2}$$
$$x_{i+1} = x_i + \frac{h}{2} \times \left(\left(-\frac{x_i^3}{2} \right) + \left(-\frac{k_1^3}{2} \right) \right)$$

Example of numerical integration method: Euler's method



Remark: precision vs performance in the application of Euler's method.

Goal of the guaranteed numerical integration

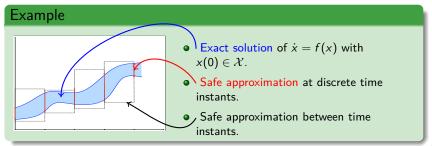
Set of solutions of IVP

We consider $\dot{x} = f(x)$, $x(0) \in \mathbf{x_0}$ with $\mathbf{x_0} \in \mathbb{IR}^n$. Solutions: $\mathcal{X} = \{x \mid x_0 \in \mathbf{x_0} \text{ such that } x \text{ is solution of } \dot{x} = f(x), x(0) = x_0\}$

Problem

Find a sequence of values (t_n, x_n) such that

$$\forall x \in \mathcal{X}, \forall n, x(t_n) \in \mathbf{x_n}$$



Guaranteed numerical integration: Taylor methods





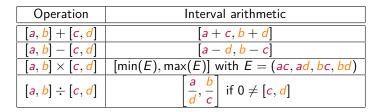
- Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

One slide on interval analysis

- Interval analysis extends arithmetic operations and elementary functions to intervals.
- Inclusion function:

$$\forall \mathbf{x} \in [\mathbf{x}], \ f(\mathbf{x}) \in [f]([\mathbf{x}]).$$



Remark: substituting all operations in the definition of a function by their interval counter-part generates an inclusion function

Guaranteed integration with Taylor method

Basics

- Assume $x(t_n) \in [x_n]$ and $h_{n+1} = t_{n+1} t_n$.
- The Taylor expansion of x :

$$\begin{aligned} x(t_{n+1}) &= x(t_n) + \sum_{i=1}^{N-1} \frac{h_{n+1}^i}{i!} \frac{d^i x}{dt^i}(t_n) + \frac{h_{n+1}^N}{N!} \frac{d^N x}{dt^N}(t') \\ &\in [\mathbf{x}_n] + \sum_{i=1}^{N-1} h_{n+1}^i f^{[i-1]}(x(t_n)) + h_{n+1}^N f^{[N-1]}(x(\xi)) \\ &\in [\mathbf{x}_n] + \sum_{i=1}^{N-1} h_{n+1}^i [f^{[i-1]}]([\mathbf{x}_n]) + h_{n+1}^N [f^{[N-1]}]([\mathbf{\tilde{x}}_n]) \triangleq \mathbf{x}_{n+1} \end{aligned}$$

Challenges

• Compute $[\tilde{\mathbf{x}}_n]$ such that $\forall t \in [t_n, t_{n+1}], x(t) \in [\tilde{\mathbf{x}}_n]$. (Solution: Picard-Lindelöf operator and Banach fixpoint theorem)

• Note that,
$$w([\boldsymbol{x}_{n+1}]) \geq w([\boldsymbol{x}_n)].$$

Banach fixpoint theorem and Picard-Lindelöf operator

To bound the term $f^{(N+1)}(x(\xi))$ requires to know a bound of the solution $x(t; x_0)$ on $[t_n, t_{n+1}]$.

Banach fixed-point theorem

Let (K, d) a complete metric space and let $g : K \to K$ a contraction that is for all x, x in K there exists $c \in]0, 1[$ such that $d(g(x), g(x)) \leq c \cdot d(x, x)$, then g has a unique fixed-point in K.

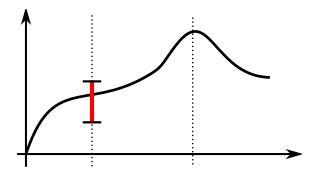
Picard-Lindelöf operator

$$P(f;t_n;x_n)(t) = x_n + \int_{t_n}^t f(x(s)) ds$$

Remark: using interval arithmetic we can compute by iteration a solution of the Picard-Lindelöf operator.

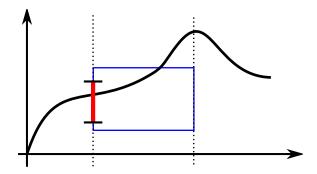
• We use the interval Picard-Lindelöf operator:

$$\Psi(\boldsymbol{R}) = \boldsymbol{x}_n + [0,h].[f](\boldsymbol{R})$$



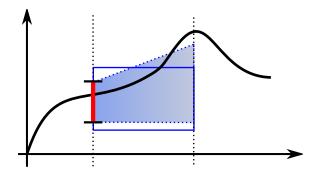
• We use the interval Picard-Lindelöf operator:

$$\Psi(\boldsymbol{R}) = \boldsymbol{x}_n + [0,h].[f](\boldsymbol{R})$$



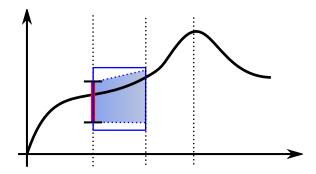
• We use the interval Picard-Lindelöf operator:

$$\Psi(\boldsymbol{R}) = \boldsymbol{x}_n + [0,h].[f](\boldsymbol{R})$$



• We use the interval Picard-Lindelöf operator:

$$\Psi(\boldsymbol{R}) = \boldsymbol{x}_n + [0,h].[f](\boldsymbol{R})$$



Reduction of the width of $[x_{n+1}]$.

We want to evaluate:

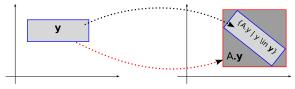
$$[\mathbf{x}_{n+1}] \triangleq [\mathbf{x}_n] + \sum_{i=1}^{N-1} h_{n+1}^i [f^{[i-1]}]([\mathbf{x}_n]) + h_{n+1}^N [f^{[N-1]}]([\tilde{\mathbf{x}}_n])$$
(2)

• To reduce the width of $[\mathbf{x}_{n+1}]$, we use centered form to compute $f^{[i]}(\mathbf{x}_n)$.

$$f([\mathbf{x}]) \in f(m([\mathbf{a}])) + J(f, [\mathbf{a}]).([\mathbf{a}] - m(\mathbf{a}))$$

After rewriting we get a linear expressions of the form: $[\mathbf{x}_{n+1}] = \mathbf{v}_n + \mathbf{A}_n \mathbf{r}_n$

• Fighting the wrapping effect (Löhner's method):



Motivation for new guaranteed integration methods

- Benefit of the well-known properties of Runge-Kutta methods, e.g.
 - Stability: A-stable, L-Stable, Algebraic stable;
 - Avoid spurious fixed-point;
 - Preservation of algebraic invariant, e.g.,:

 $\dot{\mathbf{x}} = f(t,\mathbf{x})$ with $x(0) = \mathbf{x}_0$ and such that $g(\mathbf{x}(t);\mathbf{x}_0) = 0 orall t \geq 0$

• A better adoption of the guaranteed integration methods by the engineers

Representation of sets of values





2 Numerical solution of IVP

- Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

Representation of sets

• Extension of interval arithmetic to reduce the dependency issue.

$$[a, b] + [c, d] = [a + c, b + d]$$

 $x = [0, 1] \Rightarrow x - x = [-1, 1]$

 Main idea: parametric variables w.r.t. a set of noise symbols ε_i with ε_i ∈ [-1, 1].

$$x = x_0 + x_1\varepsilon_1 + x_3\varepsilon_3$$

$$y = y_0 + y_1\varepsilon_1 + y_2\varepsilon_2$$

- This representation encodes the linear relation between noise symbols and variables and allows for precise linear transformation.
- What is a noise symbol ?
 - Initial uncertainty: $[a, b] \rightarrow \frac{a+b}{2} + \frac{b-a}{2}\varepsilon$
 - Non-linear operations and round-off errors.

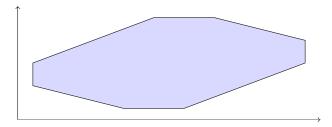
Geometric representation

Given *m* variables x^1, x^2, \ldots, x^m , an affine set

$$x^j = x_0^j + \sum_{i=1}^n x_i^j \varepsilon_i$$

is a zonotope $Z = \gamma(x^1, \ldots, x^m)$.

Example: $x = 20 - 4\varepsilon_1 + 2\varepsilon_3 + 3\varepsilon_4$ $y = 10 - 2\varepsilon_1 + \varepsilon_2 - \varepsilon_4$



Affine sets arithmetic Linear operations

Given an affine set

$$x = x_0 + \sum_{i=1}^n x_i \varepsilon_i \qquad \qquad y = y_0 + \sum_{i=1}^n y_i \varepsilon_i$$

• Affine operations: α, β, γ are constants

$$\alpha \mathbf{x} + \beta \mathbf{y} + \gamma = \alpha \mathbf{x}_0 + \beta \mathbf{y}_0 + \gamma \sum_{i=1}^n (\alpha \mathbf{x}_i + \beta \mathbf{y}_i) \varepsilon_i$$

Multiplication

$$\begin{aligned} x \times y &= x_0 y_0 + \sum_{i=1}^n (y_0 x_i + x_0 y_i) \varepsilon_i + \sum_{i=1}^n x_i \varepsilon_i \sum_{i=1}^n y_i \varepsilon_i \\ &= x_0 y_0 + \sum_{i=1}^n (y_0 x_i + x_0 y_i) \varepsilon_i + r_{n+1} \varepsilon_{n+1} \end{aligned}$$

- Other operations (sin, cos, ...) are computed using Taylor series.
- Union, intersection and inclusion test can also be defined.

Implementation

Goal of the implementation

- Sound with respect to floating-point operations.
- efficient by limiting the number of noise symbols.

Floating-point operations:

- when we add two coefficients x_i and y_i , the result is approximated.
- we want to measure and collect this error
- error free transformations: error e attached to $a \oplus b$ is

$$e = (a \ominus (s \ominus (s \ominus a))) \oplus (b \ominus (s \ominus a))$$
.

• collect the error: each time $e \neq 0$, we create a new noise symbol.

Implementation

Goal of the implementation

- Sound with respect to floating-point operations.
- e Efficient by limiting the number of noise symbols.

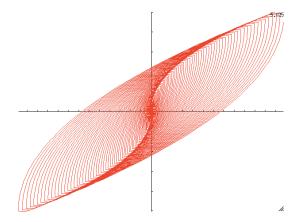
Efficiency:

- one new symbol per non-linear computation and error-prone floating-point operation.
- we chose a **sparse** representation of the coefficients attached to each variable.
- we only keep coefficients that are larger than a given threshold. \rightarrow others are **accumulated** into a new noise symbol.

Examples: the strength of affine forms

Double integrators:

$$\ddot{x} = u$$
 with $x(0) = 0$, $\dot{x}(0) = 0$, $u \in [-1, 1]$



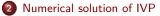
Examples: the strength of affine forms

Oscillator:

$$\dot{x} = -v$$
 $\dot{v} = x - u$ with $x(0) = 0$, $v(0) = 0$, $u \in [-1, 1]$

Guaranteed numerical integration: Runge-Kutta methods





- Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

Runge-Kutta methods

s-stage Runge-Kutta methods are described by a Butcher tableau:

Which induces the following recurrence:

$$k_i = f\left(t_n + c_i h_n, x_n + h \sum_{j=1}^s a_{ij} k_j\right)$$
 $x_{n+1} = x_n + h \sum_{i=1}^s b_i k_i$ (3)

- **Explicit** method (ERK) if $a_{ij} = 0$ is $i \leq j$
- Diagonal Implicit method (DIRK) if a_{ij} = 0 is i ≤ j and at least one a_{ii} ≠ 0
- Singly Diagonal implicit method (SDIRK) if $a_{ij} = 0$ is $i \le j$ and all $a_{ii} = \gamma$ are identical.
- Implicit method (IRK) otherwise

Examples of Runge-Kutta methods: ERK

Single-step fixed step-size explicit Runge-Kutta method

e.g. Euler's method is defined by:

$$k_1 = f(t_n, x_n)$$
$$x_{n+1} = x_n + h\mathbf{1}k_1$$



e.g. Heun's method is defined by:

$$k_{1} = f(t_{n}, x_{n})$$

$$k_{2} = f(t_{n} + h_{n}, x_{n} + h1k_{1})$$

$$x_{n+1} = x_{n} + h\left(\frac{1}{2}k_{1} + \frac{1}{2}k_{2}\right)$$



Examples of Runge-Kutta methods: ERK

Single-step variable step-size explicit Runge-Kutta method

e.g. Bogacki-Shampine (ode23) is defined by:

$$k_{1} = f(t_{n}, x_{n})$$

$$k_{2} = f(t_{n} + \frac{1}{2}h_{n}, x_{n} + \frac{1}{2}hk_{1})$$

$$k_{3} = f(t_{n} + \frac{3}{4}h_{n}, x_{n} + \frac{3}{4}hk_{2})$$

$$x_{n+1} = x_{n} + h\left(\frac{2}{9}k_{1} + \frac{1}{3}k_{2} + \frac{4}{9}k_{3}\right)$$

$$k_{4} = f(t_{n} + 1h_{n}, x_{n+1})$$

$$z_{n+1} = x_{n} + h\left(\frac{7}{24}k_{1} + \frac{1}{4}k_{2} + \frac{1}{3}k_{3} + \frac{1}{8}k_{4}\right)$$

$$(1) = \frac{1}{2}$$

$$\frac{1}{2}$$

Remark: the step-size *h* is adapted following $||x_{n+1} - z_{n+1}||$

Examples of Runge-Kutta methods: IRK

Single-step fixed step-size implicit Runge-Kutta method

e.g. Runge-Kutta Gauss method (order 4) is defined by:

$$k_{1} = f\left(t_{n} + \left(\frac{1}{2} - \frac{\sqrt{3}}{6}\right)h_{n}, \quad x_{n} + h\left(\frac{1}{4}k_{1} + \left(\frac{1}{4} - \frac{\sqrt{3}}{6}\right)k_{2}\right)\right)$$
(4a)

$$k_{2} = f\left(t_{n} + \left(\frac{1}{2} + \frac{\sqrt{3}}{6}\right)h_{n}, \quad x_{n} + h\left(\left(\frac{1}{4} + \frac{\sqrt{3}}{6}\right)k_{1} + \frac{1}{4}k_{2}\right)\right)$$
(4b)

$$x_{n+1} = x_{n} + h\left(\frac{1}{2}k_{1} + \frac{1}{2}k_{2}\right)$$
(4c)

Remark: A non-linear system of equations must be solved at each step.

Remark 2: this kind of methods is not considered here.

Bounding the truncation error¹

Goal: to bound the truncation error $||x(t_i; x_0) - x_i||$

Order condition of Runge-Kutta method

A method is of order p iff the p + 1 first coefficients of the Taylor expansion of the solution and the Taylor expansion of the numerical methods are equal.

The truncation error is defined by:

$$x(t_{n};x_{0}) - x_{n} = \frac{h_{n}^{p+1}}{(p+1)!} \left(f^{(p)}(\xi,x(\xi)) - \frac{d^{p+1}\phi}{dt^{p+1}}(\eta) \right)$$

$$\xi \in]t_{k}, t_{k+1}[\text{ and } \eta \in]t_{n}, t_{n+1}[. (5)$$

with $\phi(t) = x_n + (t - t_n) \sum_{i=1}^{s} b_i k_i(t)$.

Problem: bounding the term $f^{(p)}(\xi, x(\xi))$ (**Solution**: Picard-Lindelöf operator)

¹"Enclosing Temporal Evolution of Dynamical Systems Using Numerical Methods", NFM'13

Main algorithm

- Input:
 - a Butcher tableau of the explicit Runge-Kutta methods
 - the order *p* of the method
 - the problem f to solve s.t. $\dot{\mathbf{x}} = f(\mathbf{x})$
 - the initial conditions [x₀]
- Preliminaries:
 - Compute the *p*-th derivatives of *f*
 - Compute the p+1-th derivatives of ϕ
- The main steps are (in a loop):
 - **9** From $[\mathbf{x}_n]$ apply explicit Runge-Kutta methods ϕ to compute $[\hat{\mathbf{x}}_{n+1}]$
 - Apply Picard-Lindelöf to compute [x]
 - ${f 0}$ If truncation error E below of a tolerance arepsilon then goto 5
 - Else reduce step-size h/2 and goto 1

3
$$[\mathbf{x}_{n+1}] = [\hat{\mathbf{x}}_{n+1}] + E$$
 and

• update step-size h in function to E and goto 1

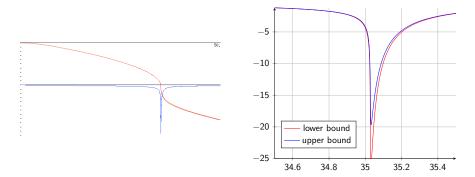
Remark: even fixed-step explicit Runge-Kutta methods are transformer into variable-step guaranteed methods.

Example: a chemical reaction

Consider the IVP:

$$\begin{cases} \dot{y} = z \\ \dot{z} = z^2 - \frac{3}{0.001 + y^2} \end{cases} \text{ with } \begin{cases} y(0) = 10 \\ z(0) = 0 \end{cases}$$

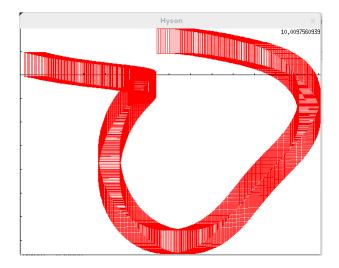
It admits a discontinuity in the solution around t = 35.



Example: sail boat

```
init x = [0,1];
init y = [0,1]; # initial position
init theta = 0:
init deltav = 0.5;
init deltag = 0;
init v = 2;
init omega = 0;
u1 = -0.5;
u2 = 0:
# Physical model
x' = v * cos(theta):
v' = v * sin(theta) - beta * vent;
theta' = omega;
deltav' = u1:
deltag' = u2;
v' = (fv * sin(deltav) - fg * sin(deltag) - alphaf * v) / m;
omega' = (fv * (long - rv * cos(deltav)) -
             rg * fg * cos(deltag) - alphatheta * omega) / j;
fv=alphav*vent*cos(theta+deltav)-alphav*v*sin(deltav);
fg=alphag*vitesse*sin(deltag);
output(x,y);
```

Example: sail boat



Conclusion



- 2 Numerical solution of IVP
- 3 Guaranteed numerical integration: Taylor methods
- 4 Representation of sets of values
- 5 Guaranteed numerical integration: Runge-Kutta methods

6 Conclusion

Conclusion

Guaranteed numerical solution of IVP based on:

- affine arithmetic
- well known numerical scheme: explicit Runge-Kutta methods

Future work

- Consider implicit Runge-Kutta methods.
- Consider multi-step methods as Adams-Bashworth, BDF, etc.
- Consider DAE e.g., $F(x, \dot{x}, y) = 0$.
- Consider delayed differential equations.