

# Génération et validation des méthodes de Runge-Kutta

Overview of four years of study Alexandre Chapoutot, Julien Alexandre dit Sandretto



Department U2IS

ENSTA ParisTech

RAIM 2018 - Gif-sur-Yvette

#### Context

#### Interval Analysis

Arithmetic and sets Constraint Satisfaction Problem

#### Validated Simulation

Simulation of IVP Validated simulation

#### Validated Runge-Kutta Methods

Validated schemes Local Truncation Error Computation of validated RK Examples

#### Differential constraint satisfaction problems

#### Constraint Programming and Runge-Kutta

CSP to define RK Experimentations Cost function to define optimal schemes Experimentations Properties

#### Conclusion



### Robot's behavior

#### ENSTA ParisTech. Universite

#### A mobile robot...



- ► ... moves! ⇒ Dynamical system (discrete, continuous, switched, hybrid, etc)
- $\blacktriangleright$  drived by actuators  $\Rightarrow$  control
- ▶ w.r.t. sensors and design parameters ⇒ uncertainties
- for critical tasks ! (in our case)

#### Control: synthesis, analysis, verification

Two antinomic facts: reliable results under uncertainties !



### $[x] = [\underline{x}, \overline{x}]$ stands for the set of reals x s.t. $\underline{x} \leq x \leq \overline{x}$

#### Arithmetic

Extension of operators (+, -, \*, /, sin, cos, ...), e.g. [-1, 1] + [1, 3] = [0, 4]Rounding error handled  $(1/3 \in 0.33333333[3, 4])$ 

### Extension of function

 $[f]([x]) \supset f([x]) = \{f(y) | y \in [x]\}$ 

### Interval Integral



$$[x] = [\underline{x}, \overline{x}]$$
 stands for the set of reals x s.t.  $\underline{x} \le x \le \overline{x}$ 

#### Arithmetic

Extension of operators (+, -, \*, /, sin, cos, ...), e.g. [-1, 1] + [1, 3] = [0, 4]Rounding error handled  $(1/3 \in 0.33333333[3, 4])$ 

#### Extension of function

 $[f]([x]) \supset f([x]) = \{f(y) | y \in [x]\}$ 

#### Interval Integral

 $[x] = [\underline{x}, \overline{x}]$  stands for the set of reals x s.t.  $\underline{x} \leq x \leq \overline{x}$ 

#### Arithmetic

Extension of operators (+, -, \*, /, sin, cos, ...), e.g. [-1, 1] + [1, 3] = [0, 4]Rounding error handled  $(1/3 \in 0.33333333[3, 4])$ 

### Extension of function



Interval Integral



 $[x] = [\underline{x}, \overline{x}]$  stands for the set of reals x s.t.  $\underline{x} \leq x \leq \overline{x}$ 

#### Arithmetic

Extension of operators (+, -, \*, /, sin, cos, ...), e.g. [-1, 1] + [1, 3] = [0, 4]Rounding error handled  $(1/3 \in 0.33333333[3, 4])$ 

Extension of function



Interval Integral





### Branch & Prune for f(x) = 0



A classical problem find x s.t. f(x) = 0 assuming  $x \in [x]$ .

#### More generally, a CSP is

- $\blacktriangleright$  a set of variables  ${\cal V}$
- $\blacktriangleright$  a set of domains  ${\cal D}$
- ► a set of constraints C.



### Branch & Prune for f(x) = 0



### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- ▶ if 0 ∈ [f]([x]) then maybe one solution in [x]



### Branch & Prune for f(x) = 0



### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- if  $0 \in [f]([x])$  then maybe one solution in [x]



### Branch & Prune for f(x) = 0



### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- If 0 ∈ [f]([x]) then maybe one solution in [x]



### Branch & Prune for f(x) = 0



### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- ▶ if 0 ∈ [f]([x]) then maybe one solution in [x]



### Branch & Prune for f(x) = 0



### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- ▶ if 0 ∈ [f]([x]) then maybe one solution in [x]



### Branch & Prune for f(x) = 0



Some improvements are available <sup>[1]</sup> [1] Jaulin et al., "Applied Interval Analysis", Springer, 2001

#### A simple method

 $\label{eq:linear} \begin{array}{l} \mbox{Interval arithmetic} + \mbox{bisection} \\ \mbox{strategy} \end{array}$ 

- If 0 ∉ [f]([x]) then no possible solution in [x]
- if  $0 \in [f]([x])$  then maybe one solution in [x]

### Simulation of IVP



Consider an IVP for ODE, over the time interval [0, T]

$$\dot{\mathbf{y}} = f(\mathbf{y})$$
 with  $\mathbf{y}(0) = \mathbf{y}_0$ 

IVP has a unique solution  $\mathbf{y}(t; \mathbf{y}_0)$  if  $f : \mathbb{R}^n \to \mathbb{R}^n$  is Lipschitz in  $\mathbf{y}$  but for our purpose we suppose f smooth enough, *i.e.*, of class  $C^k$ 

#### Numerical integration

Approximate the solution:

- Compute a sequence of time instants: t<sub>0</sub> = 0 < t<sub>1</sub> < ··· < t<sub>n</sub> = T (with a stepsize controller)
- Compute a sequence of values:  $\mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_n$  such that

$$\forall i \in \{0,\ldots,n\}, \quad \mathbf{y}_i \approx \mathbf{y}(t_i; \mathbf{y}_0) \;.$$

### Validated Simulation



### Goal of validated numerical integration

- Same discretization approach
- ▶ Compute a sequence  $[\tilde{\mathbf{y}_0}], [\tilde{\mathbf{y}_1}], \dots, [\tilde{\mathbf{y}_{n-1}}]$  such that

$$\forall i \in \{0,\ldots,n\}, \quad \mathbf{y}(t;\mathbf{y}_0) \in [\mathbf{\tilde{y}}_i], \forall t \in [t_i,t_{i+1}] ,$$

▶ and a sequence of values:  $[\mathbf{y}_0], [\mathbf{y}_1], \dots, [\mathbf{y}_n]$  such that

$$\forall i \in \{0,\ldots,n\}, \quad \mathbf{y}(t_i;\mathbf{y}_0) \in [\mathbf{y}_i] \;.$$

### Validated Simulation



### A two-step approach Exact solution of $\dot{\mathbf{y}} = f(\mathbf{y}(t)), \mathbf{y}(0) \in [\mathbf{y}_0]$ Safe approximation at discrete time instants $[\mathbf{y}_i]$ , obtained with Taylor (Capd, Vnode) or Runge-Kutta (Dynlbex) validated methods Safe approximation between time instants $[\tilde{\mathbf{y}}_i]$ , obtained with a Picard-Lindelöf operator

### Validated Simulation



### Picard-Lindelöf operator

Formal solution of ODE:  $\mathbf{y}_{n+1} = \mathbf{y}_n + \int_0^h f(s) ds$ Following the rectangle rule, based on Brouwer's theorem, the Picard-Lindelöf operator is defined such that:

 $P([\mathbf{x}]) = \mathbf{y}_{\mathbf{n}} + [0, h][f]([\mathbf{x}])$ 

- If P([x]) ⊂ Int([x]), then ODE admits one and only one solution and this solution is in [x], ∀s ∈ [0, h] (even in P([x]))
   ⇒ and [ỹ] = [x]
- Otherwise [x] is inflated, or *h* is reduced

**Remarks:** the rectangle rule can be replaced by any validated scheme (Taylor series  $^{[1]}$  or RK)

[1] Nedialkov et al., "Validated solutions of initial value problems for ordinary differential equations", Appl. Math. and Comp., 1999

## State of the art

### Taylor methods



They have been developed since 60's (Moore, Lohner, Makino and Berz, Corliss and Rhim, Neher *et al.*, Jackson and Nedialkov, etc.)

- prove the existence and uniqueness: high order interval Picard-Lindelöf
- works very well on various kinds of problems:
  - non stiff and moderately stiff linear and non-linear systems,
  - with thin uncertainties on initial conditions
  - with (a writing process) thin uncertainties on parameters
- very efficient with automatic differentiation techniques
- wrapping effect fighting: interval centered form and QR decomposition
- **many software**: AWA, COSY infinity, VNODE-LP, CAPD, etc.

#### Some extensions

- Taylor polynomial with Hermite-Obreskov (Jackson and Nedialkov)
- Taylor polynomial in Chebyshev basis (T. Dzetkulic)

### History on Interval Runge-Kutta methods



Andrzej Marciniak *et al.* work on this topic since 1999

"The form of  $\psi(t, y(t))$  is very complicated and cannot be written in a general form for an arbitrary p"

The implementation OOIRK is not freely avalaible.

- Hartmann and Petras, ICIAM 1999
   No more information than an abstract of 5 lines.
- Bouissou and Martel, SCAN 2006 (only RK4 method) Implementation GRKLib is not available
- Bouissou, Chapoutot and Djoudi, NFM 2013 (any explicit RK) Implementation is not available
- Alexandre dit Sandretto and Chapoutot, 2016 (any explicit and implicit RK) implementation DynIBEX is open-source, combine with IBEX

Validated Runge-Kutta Methods Validated schemes

### Validated Runge-Kutta methods



A validated algorithm

$$[\mathbf{y}_{\ell+1}] = [\Phi](h, [\mathbf{y}_{\ell}]) + \mathsf{Error} ext{ of } \Phi$$
 .

# Validated Runge-Kutta Methods

How validate a RK method ?



Order of Runge-Kutta methods and Local Truncation Error (LTE)

$$LTE = \mathbf{y}(t_{\ell}; \mathbf{y}_{\ell-1}) - \mathbf{y}_{\ell} = C \cdot h^{p+1}$$
 with  $C \in \mathbb{R}$ .

We need to bound the LTE with guarantee...

### Order condition

This condition states that a method of RK family is of order p iff

- the Taylor expansion of the exact solution
- and the Taylor expansion of the numerical methods

have the same p + 1 first coefficients.

### Consequence

The LTE is the difference of Lagrange remainders of 2 Taylor expansions

# Validated Runge-Kutta Methods

### Theorem 1 (Butcher, 1963)

The *q*th derivative of the **exact solution** is given by

$$\mathbf{y}^{(q)} = \sum_{r(\tau)=q} \alpha(\tau) F(\tau)(\mathbf{y}_0) \quad \text{with} \quad \begin{array}{l} r(\tau) \text{ the order of the rooted tree } \tau \\ \alpha(\tau) \text{ a positive integer} \\ F(\tau)(.) \text{ elementary differential for } \tau \end{array}$$

/ ) .1

We can do the same for the numerical solution:

### Theorem 2 (Butcher, 1963)

The *q*th derivative of the **numerical solution** is given by

$$\mathbf{y}_1^{(q)} = \sum_{r(\tau)=q} \gamma(\tau)\phi(\tau)\alpha(\tau)F(\tau)(\mathbf{y}_0) \quad \text{with} \quad \begin{array}{l} \gamma(\tau) \text{ a positive integer} \\ \phi(\tau) \text{ depending on a Butcher tableau} \end{array}$$

### Theorem 3, order condition (Butcher, 1963)

A Runge-Kutta method has order p iff  $\phi( au)=rac{1}{\gamma( au)}\quad orall au, r( au)\leqslant p$ 



# LTE formula for explicit and implicit Runge-Kutta



From Theorem 1 and Theorem 2, if a Runge-Kutta has order p then

$$\mathbf{y}(t_1; \mathbf{y}_0) - \mathbf{y}_1 = \frac{h^{p+1}}{(p+1)!} \sum_{r(\tau) = p+1} \alpha(\tau) \big[ 1 - \gamma(\tau)\phi(\tau) \big] F(\tau)(\mathbf{y}(\xi)), \quad \xi \in [t_1, t_0]$$

#### Remark

In theory, bound the LTE of a Runge-Kutta is a simpler problem:

- ▶ for each method the Butcher tableau and the order available
- $\mathbf{y}(\xi)$  is enclosed by  $[\tilde{\mathbf{y}}]$  using Picard-Lindelöf operator But complex in practice !

Two methods: direct form (symbolic derivatives and trees<sup>[1]</sup>) or factorized (automatic differentiation and graphs<sup>[2,3]</sup>)

Alexandre dit Sandretto et al., "Validated explicit and implicit Runge-Kutta methods", Reliable Computing 2016
 Bartha et al., "Computing of B-series by automatic differentiation", Discrete and continuous dynamical systems, 2014
 Mullier et al., "Validated Computation of the Local Truncation Error of Runge-Kutta Methods with Automatic Differentiation", AD 2016

# Validated Runge-Kutta Methods

 $\Rightarrow$  LTE can be bounded, but...

It remains to compute the RK scheme itself:

Explicit RK: evaluation of f with intervals Heun's scheme:

$$\begin{aligned} [\mathbf{k}_1] &= [f](t_n, [\mathbf{y}_n]) \ , \qquad [\mathbf{k}_2] &= [f](t_n + \mathbf{1}h, [\mathbf{y}_n] + h\mathbf{1}[\mathbf{k}_1]) & \mathbf{0} \\ [\mathbf{y}_{n+1}] &= [\mathbf{y}_n] + h\left(\frac{1}{2}[\mathbf{k}_1] + \frac{1}{2}[\mathbf{k}_2]\right) & \qquad \frac{1}{2} \end{aligned}$$



$$\begin{aligned} [\mathbf{k}_1] &= [f]\left(t_n + \left(\frac{1}{2} - \frac{\sqrt{3}}{6}\right)h, \quad [\mathbf{y}_n] + h\left(\frac{1}{4}[\mathbf{k}_1] + \left(\frac{1}{4} - \frac{\sqrt{3}}{6}\right)[\mathbf{k}_2]\right)\right) \\ [\mathbf{k}_2] &= [f]\left(t_n + \left(\frac{1}{2} + \frac{\sqrt{3}}{6}\right)h, \quad [\mathbf{y}_n] + h\left(\left(\frac{1}{4} + \frac{\sqrt{3}}{6}\right)[\mathbf{k}_1] + \frac{1}{4}[\mathbf{k}_2]\right)\right) \\ \mathbf{y}_{n+1}] &= [\mathbf{y}_n] + h\left(\frac{1}{2}[\mathbf{k}_1] + \frac{1}{2}[\mathbf{k}_2]\right) \end{aligned}$$



### Validated Runge-Kutta Methods



Solve a problem with interval analysis: contraction technique\*\* !  $[{\bm k}_1]=[{\bm k}_2]=[{\bm k}_3]=[{\bm k}_4]=[\tilde{{\bm y}}]$  Then, we repeat:

$$\begin{bmatrix} \mathbf{k}_1 \end{bmatrix} = \begin{bmatrix} \mathbf{k}_1 \end{bmatrix} \cap \begin{bmatrix} f \end{bmatrix} \left( \begin{bmatrix} \mathbf{y}_n \end{bmatrix} + h \left( \frac{1}{4} \begin{bmatrix} \mathbf{k}_1 \end{bmatrix} + \left( \frac{1}{4} - \frac{\sqrt{3}}{6} \right) \begin{bmatrix} \mathbf{k}_2 \end{bmatrix} \right) \right)$$
$$\begin{bmatrix} \mathbf{k}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{k}_2 \end{bmatrix} \cap \begin{bmatrix} f \end{bmatrix} \left( \begin{bmatrix} \mathbf{y}_n \end{bmatrix} + h \left( \left( \frac{1}{4} + \frac{\sqrt{3}}{6} \right) \begin{bmatrix} \mathbf{k}_1 \end{bmatrix} + \frac{1}{4} \begin{bmatrix} \mathbf{k}_2 \end{bmatrix} \right) \right)$$

\*\* *f* is contracting on  $[\tilde{\mathbf{y}}]$  because of Picard-Lindelöf success (if  $c_i \leq 1$ )...

Provides a **tube**, abstracted by a list of boxes  $([\mathbf{y}_i], [\tilde{\mathbf{y}}_i])$ : Initial states: y(0) = (0; -10.3; 0.03), some parameters: a = 0.2, b = 0.2, c = 5.7

The differential system:  $\dot{y} = \begin{cases} -(y_1 + y_2) \\ y_0 + a * y_1 \\ b + y_2 * (y_0 - c) \end{cases}$ 



### A chemical reaction simulated (stiff)

$$\begin{cases} \dot{y} = z \\ \dot{z} = z^2 - \frac{3}{0.0001 + y^2} \end{cases} \quad \text{with} \quad \begin{cases} y(0) = 10 \\ z(0) = 0 \end{cases} \quad \text{and} \quad t \in [0, 50] \end{cases}$$

**Result:** Taylor based tools fail around t = 1 (order 5 to 40). With validated Lobatto-IIIC (order 4), tolerance  $10^{-10}$ , solved in 7.6s





#### Van Der Pol 50s

Initial states: y(0) = (2,0), One parameter:  $\mu = 1.0$  or 2.0

$$\dot{y} = \begin{cases} y_1 \\ \mu * (1 - y_0^2) * y_1 - y_0 \end{cases}$$





#### Volterra 6s

Initial states: y(0) = (1.0; 3.0)The differential system:  $\dot{y} = \begin{cases} 2 * y_0 * (1 - y_1) \\ -y_1 * (1 - y_0) \end{cases}$ 





# Circle 100s Initial states: y(0) = ([0, 0.1]; [0.95, 1.05])The differential system: $\dot{y} = \begin{cases} -y_1 \\ y_0 \end{cases}$





### Dynamical systems



A general settings of dynamical systems

$$S \equiv \begin{cases} \dot{\mathbf{y}}(t) = \mathbf{f}(t, \mathbf{y}(t), \mathbf{x}(t), \mathbf{p}), \\ 0 = \mathbf{g}(t, \mathbf{y}(t), \mathbf{x}(t)) \\ 0 = \mathbf{h}(\mathbf{y}(t), \mathbf{x}(t)) \end{cases}.$$

we denote by

$$\mathcal{Y}(\mathcal{T},\mathcal{Y}_0,\mathcal{P}) = \{ \mathbf{y}(t;\mathbf{y}_0,\mathbf{p}) : t \in \mathcal{T}, \mathbf{y}_0 \in \mathcal{Y}_0, \mathbf{p} \in \mathcal{P} \}$$

the set of solutions

### Example of ODEs with constraints

Production-Destruction systems based on an ODE with parameter a = 0.3

$$\begin{pmatrix} \dot{y}_{0} \\ \dot{y}_{1} \\ \dot{y}_{2} \end{pmatrix} = \begin{pmatrix} \frac{-y_{0}y_{1}}{1+y_{0}} \\ \frac{y_{0}y_{1}}{1+y_{0}} - ay_{1} \\ ay_{1} \end{pmatrix}$$

and associated to constraints:

$$y_0 + y_1 + y_2 = 10.0$$
  
 $y_0 \ge 0$   
 $y_1 \ge 0$   
 $y_2 \ge 0$ 

Initial values, for  $t \in [0, 100]$ , are

$$\begin{pmatrix} y_0(0) \\ y_1(0) \\ y_2(0) \end{pmatrix} = \begin{pmatrix} 9.98 \\ 0.01 \\ 0.01 \end{pmatrix}$$



Differential constraint satisfaction problems

## ODEs with constraints in DynIBEX - results





# Constraint Satisfaction Differential Problems

### CSDP



Let S be a differential system and  $t_{\rm end} \in \mathbb{R}_+$  the time limit. A CSDP is a NCSP defined by

- ▶ a finite set of variables V including the parameters of the differential systems S<sub>i</sub>, *i.e.*, (y<sub>0</sub>, p), a time variable t and some other algebraic variables q;
- ▶ a domain D made of the domain of parameters p : D<sub>p</sub>, of initial values y<sub>0</sub> : D<sub>y₀</sub>, of the time horizon t : D<sub>t</sub>, and the domains of algebraic variables D<sub>q</sub>;
- ▶ a set of constraints C which may be defined by set-based constraints over variables of V and special variables Y<sub>i</sub>(D<sub>t</sub>, D<sub>y0</sub>, D<sub>p</sub>) representing the set of the solution of S<sub>i</sub> in S.

with set-based constraints considered:

$$\begin{array}{ll} \mathbf{g}(\mathcal{A}) \subseteq \mathcal{B} & \qquad \mathbf{g}(\mathcal{A}) \supseteq \mathcal{B} \\ \mathbf{g}(\mathcal{A}) \cap \mathcal{B} = \emptyset & \qquad \mathbf{g}(\mathcal{A}) \cap \mathcal{B} \neq \emptyset \end{array}$$

# Particular problems considered and temporal propertie

We focus on particular problems of robotics involving quantifiers

- ▶ Robust controller synthesis:  $\exists u$ ,  $\forall p$ ,  $\forall y_0$  + temporal constraints
- ▶ Parameter synthesis:  $\exists \mathbf{p}, \forall \mathbf{u}, \forall \mathbf{y}_0 + \text{temporal constraints}$

etc.

We also defined a set of temporal constraints useful to analyze/design robotic application.

Verbal property	QCSDP translation
Stay in ${\cal A}$	$orall t \in [0, t_{end}],  [\mathbf{y}](t, \mathbf{v}') \subseteq Int(\mathcal{A})$
In ${\cal A}$ at $ au$	$\exists t \in [0, t_{end}],  [\mathbf{y}](t, \mathbf{v}') \subseteq Int(\mathcal{A})$
Has crossed $\mathcal{A}^{oldsymbol{st}}$	$\exists t \in [0, t_{end}], \ [\mathbf{y}](t, \mathbf{v}') \cap Hull(\mathcal{A}) \neq \emptyset$
Go out ${\mathcal A}$	$\exists t \in [0, t_{end}], \ [\mathbf{y}](t, \mathbf{v}') \cap Hull(\mathcal{A}) = \emptyset$
Has reached $\mathcal{A}^{oldsymbol{st}}$	$[\mathbf{y}](t_{end},\mathbf{v}')\capHull(\mathcal{A}) eq\emptyset$
Finished in ${\cal A}$	$[\textbf{y}](\textit{t}_{end},\textbf{v}')\subseteqInt(\mathcal{A})$

\*: shall be used in negative form

Differential constraint satisfaction problems

# One application: validated path planning





# Second part

Context

#### Interval Analysis

Arithmetic and sets Constraint Satisfaction Problem

#### Validated Simulation

Simulation of IVP Validated simulation

#### Validated Runge-Kutta Methods

Validated schemes Local Truncation Error Computation of validated RK Examples

#### Differential constraint satisfaction problems

#### Constraint Programming and Runge-Kutta

CSP to define RK Experimentations Cost function to define optimal schemes Experimentations Properties

Conclusion



Constraint Programming and Runge-Kutta CSP to define RK

#### ENSTA ParisTech universite PARISTECH

# Constraint Programming and Runge-Kutta

#### Is it possible to define new RK schemes with IA tools ?

- + Higher order implies smaller LTE
- + Method adapted to a given problem
- Coefficients must be computed with guarantee too !

### New scheme: a complex problem

#### Needs to solve constraints

High order polynomials (till *p*), number of constraints increases rapidly (4 for *p* = 3, 8 for *p* = 4, 17, 37, 85, 200)  $1.\sum_{1}^{s} b_{i} = 1$   $2.\sum_{1}^{s} b_{i}c_{i} = 1/2$  $3.\sum_{1}^{s} b_{i}c_{i}^{2} = 1/3$   $\sum_{1}^{s} \sum_{1}^{s} b_{i}a_{ij}c_{j} = 1/6$ 

### Classical approach

Solved by using polynomials with known exact zeros such as Legendre (for Gauss) or Jacobi (for Radau)

### Problems

- Discovery of new methods guided by solver and not by requirements
- Solved numerically: additive approximations
  - Constraints not satisfied  $\Rightarrow$  Method not at order *p*, but lower...
  - Validated methods use LTE: wrong with floating numbers



### New scheme: a complex problem

#### Needs to solve constraints

High order polynomials (till *p*), number of constraints increases rapidly (4 for *p* = 3, 8 for *p* = 4, 17, 37, 85, 200)  $1.\sum_{1}^{s} b_{i} = 1$   $2.\sum_{1}^{s} b_{i}c_{i} = 1/2$  $3.\sum_{1}^{s} b_{i}c_{i}^{2} = 1/3$   $\sum_{1}^{s} \sum_{1}^{s} b_{i}a_{ij}c_{j} = 1/6$ 

### Classical approach

Solved by using polynomials with known exact zeros such as Legendre (for Gauss) or Jacobi (for Radau)

### Problems

- Discovery of new methods guided by solver and not by requirements
- Solved numerically: additive approximations
  - Constraints not satisfied  $\Rightarrow$  Method not at order *p*, but lower...
  - Validated methods use LTE: wrong with floating numbers



### New scheme: a complex problem

#### Needs to solve constraints

High order polynomials (till *p*), number of constraints increases rapidly (4 for *p* = 3, 8 for *p* = 4, 17, 37, 85, 200)  $1.\sum_{1}^{s} b_{i} = 1$   $2.\sum_{1}^{s} b_{i}c_{i} = 1/2$  $3.\sum_{1}^{s} b_{i}c_{i}^{2} = 1/3$   $\sum_{1}^{s} \sum_{1}^{s} b_{i}a_{ij}c_{j} = 1/6$ 

### Classical approach

Solved by using polynomials with known exact zeros such as Legendre (for Gauss) or Jacobi (for Radau)

#### Problems

- Discovery of new methods guided by solver and not by requirements
- Solved numerically: additive approximations
  - Constraints not satisfied  $\Rightarrow$  Method not at order *p*, but lower...
  - Validated methods use LTE: wrong with floating numbers



Constraint Programming and Runge-Kutta CSP to define RK

# Constraint approach to define new schemes

#### Constraints:

#### Consistency

- $\triangleright$   $c_i = \sum a_{ii}$  with  $c_1 < \cdots < c_s$ Order conditions
- Function of order of desired method, example  $\sum c_i b_i a_{ii} - 1/6 = 0$

# 

- Singly diagonal:  $a_{1,1} = \cdots = a_{s,s}$
- Explicit:  $a_{ii} = 0, \forall j \ge i$
- ▶ Diagonal implicit:  $a_{ii} = 0, \forall i > i$
- Explicit first line:  $a_{1,1} = \cdots = a_{1,s} = 0$
- Stiffly accurate:  $a_{s,i} = b_i, \forall i = 1, \dots, s$

Variables: Butcher

tableau coefficients

**Domains:**  $c_i \in [0, 1]$ ,

(a subpart)

 $b_i \in [-1, 1], a_{ij} \in [-1, 1]$ 

 $c_1 a_{11} a_{12} \cdots a_{1s}$ 



# Re-discover the theory

#### Only one 2-stage method of order 4

```
Variables
b[2] in [-1.1]:
c[2] in [0,1];
a[2][2] in [-1,1];
Constraints
b(1) +b(2) -1.0=0;
b(1)*c(1) + b(2)*c(2) - 1.0/2.0=0:
b(1)*(c(1))^2 + b(2)*(c(2))^2 - 1.0/3.0=0:
b(1)*a(1)(1)*c(1) + b(1)*a(1)(2)*c(2) +
    b(2)*a(2)(1)*c(1) +b(2)*a(2)(2)*c(2)
    -1.0/6.0=0:
b(1)*(c(1))^3 + b(2)*(c(2))^3 - 1.0/4.0=0:
b(1)*c(1)*a(1)(1)*c(1) + b(1)*c(1)*a(1)(2)*c(2) +
    b(2)*c(2)*a(2)(1)*c(1) +b(2)*c(2)*a(2)(2)*c(2)
    -1.0/8.0=0:
b(1)*a(1)(1)*(c(1))^2 + b(1)*a(1)(2)*(c(2))^2 +
    b(2)*a(2)(1)*(c(1))^2 + b(2)*a(2)(2)*(c(2))^2
    -1.0/12.0=0:
b(1)*a(1)(1)*a(1)(1)*c(1) + b(1)*a(1)(1)*a(1)(2)*c(2) +
    b(1)*a(1)(2)*a(2)(1)*c(1) +b(1)*a(1)(2)*a(2)(2)*c(2) +
    b(2)*a(2)(1)*a(1)(1)*c(1) +b(2)*a(2)(1)*a(1)(2)*c(2) +
    b(2)*a(2)(2)*a(2)(1)*c(1) +b(2)*a(2)(2)*a(2)(2)*c(2)
    -1.0/24.0=0:
a(1)(1)+a(1)(2)-c(1) = 0; a(2)(1)+a(2)(2)-c(2) = 0;
c(1) < c(2):
end
```

#### Solved with Ibex

number of solutions=1 cpu time used=0.013073s. ([0.5, 0.5]; [0.5, 0.5]; 0.21132486640[5,6]; 0.78867513459[5,6]\$ [0.25, 0.25]; -0.038675134594[9,8] 0.538675134594[5,6]; [0.25, 0.25])



# Re-discover the theory

#### ENSTA ParisTech PARIS-SACLAY

#### Only one 2-stage method of order 4

```
Variables
b[2] in [-1.1]:
c[2] in [0,1];
a[2][2] in [-1,1];
Constraints
b(1) +b(2) -1.0=0;
b(1)*c(1) + b(2)*c(2) - 1.0/2.0=0:
b(1)*(c(1))^2 + b(2)*(c(2))^2 - 1.0/3.0=0:
b(1)*a(1)(1)*c(1) + b(1)*a(1)(2)*c(2) +
    b(2)*a(2)(1)*c(1) +b(2)*a(2)(2)*c(2)
    -1.0/6.0=0:
b(1)*(c(1))^3 + b(2)*(c(2))^3 - 1.0/4.0=0:
b(1)*c(1)*a(1)(1)*c(1) + b(1)*c(1)*a(1)(2)*c(2) +
    b(2)*c(2)*a(2)(1)*c(1) +b(2)*c(2)*a(2)(2)*c(2)
    -1.0/8.0=0:
b(1)*a(1)(1)*(c(1))^2 + b(1)*a(1)(2)*(c(2))^2 +
    b(2)*a(2)(1)*(c(1))^2 + b(2)*a(2)(2)*(c(2))^2
    -1.0/12.0=0:
b(1)*a(1)(1)*a(1)(1)*c(1) + b(1)*a(1)(1)*a(1)(2)*c(2) +
    b(1)*a(1)(2)*a(2)(1)*c(1) +b(1)*a(1)(2)*a(2)(2)*c(2) +
    b(2)*a(2)(1)*a(1)(1)*c(1) +b(2)*a(2)(1)*a(1)(2)*c(2) +
    b(2)*a(2)(2)*a(2)(1)*c(1) +b(2)*a(2)(2)*a(2)(2)*c(2)
    -1.0/24.0=0:
a(1)(1)+a(1)(2)-c(1) = 0; a(2)(1)+a(2)(2)-c(2) = 0;
c(1) < c(2):
end
```

#### Solved with Ibex

number of solutions=1 cpu time used=0.013073s. ((0.5, 0.5]; [0.5, 0.5]; 0.21132486540[5,6]; 0.78867513459[5,6]\$ [0.25, 0.25]; -0.038675134594[9,8] 0.538675134594[9,6]; [0.25, 0.25])

#### $\Rightarrow$ Validated Gauss-Legendre !

Experimentations

Re-discover the theory and ...



### No 2-stage method of order 5 Proof in 0.04s !

...find new methods Remark: it is hard to be sure that a method is new...

# A method order 4, 3 stages, singly, stiffly accurate



This method is promising: capabilities wanted for a stiff problem, singly to optimize the Newton solving and stiffly accurate to be more efficient w.r.t. stiff problems (and DAEs).

0.1610979566[59, 62]	0.105662432[67, 71]	0.172855006[54,67]	-0.117419482[69, 58]
0.655889341[44, 50]	0.482099622[04, 10]	0.105662432[67, 71]	0.068127286[68, 74]
[1, 1]	0.3885453883[37,75]	0.5057921789[56, 65]	0.105662432[67,71]
	0.3885453883[37,75]	0.5057921789[56, 65]	0.105662432[67, 71]

Table: New method S3O4

### Integration with the new schemes



Implemented in Dynlbex (a tool for validated simulation) Norm of diameter of final solution bounds the global error

Methods	time (s)	nb of steps	norm of diameter of final solution
S3O4	39	1821	$5.9 \cdot 10^{-5}$
Radau3	52	7509	$2 \cdot 10^{-4}$
Radau5	81	954	$7.6 \cdot 10^{-5}$

Table: S3O4 on a stiff problem (oil problem)

 $\Rightarrow$  As efficient than Radau at order 5, but faster than order 3 !

# Cost function to define optimal schemes



### Problem: continuum of solutions

CSP can be under constrained (e.g.,  $p \leq s$ )

### Example of countless methods

Countless number of 2-stage; order 2; stiffly accurate; fully implicit

#### Optimization

- ► We could find the best one!
- How choose the cost function?

## Cost function to define optimal schemes



### Problem: continuum of solutions

CSP can be under constrained (e.g.,  $p \leq s$ )

### Example of countless methods

Countless number of 2-stage; order 2; stiffly accurate; fully implicit

#### Optimization

- We could find the best one!
- How choose the cost function?

## Cost function to define optimal schemes



### Problem: continuum of solutions

CSP can be under constrained (e.g.,  $p \leq s$ )

### Example of countless methods

Countless number of 2-stage; order 2; stiffly accurate; fully implicit

#### Optimization

- We could find the best one!
- How choose the cost function?

### Cost function



### Minimizing local truncation error

- Method with lower error for the same order
- Example of general form of ERK with 2 stages and order 2

Ralston[1]:  $\alpha=2/3$  minimizes the sum of square of coefficients of rooted trees in the lte computation

#### Our approach: maximizing the order

- Minimizing the sum of squares of order constraints
- Cost easy to compute: direct from constraints

Same result  $\alpha \in [0.666...6, 0.666...7]$  !

[1] Ralston, Anthony. "Runge-Kutta methods with minimum error bounds." Mathematics of computation (1962).

### Cost function



### Minimizing local truncation error

- Method with lower error for the same order
- Example of general form of ERK with 2 stages and order 2

$$\begin{array}{c|cccc}
0 & 0 & 0 \\
\alpha & \alpha & 0 \\
\hline
& 1-1/(2 \alpha) & 1/(2 \alpha)
\end{array}$$

Ralston[1]:  $\alpha=2/3$  minimizes the sum of square of coefficients of rooted trees in the lte computation

#### Our approach: maximizing the order

- Minimizing the sum of squares of order constraints
- Cost easy to compute: direct from constraints
- Same result  $\alpha \in [0.666...6, 0.666...7]$  !

[1] Ralston, Anthony. "Runge-Kutta methods with minimum error bounds." Mathematics of computation (1962).

### Re-discover the theory



#### Theory

Countless 2-stage order 2 stiffly accurate fully implicit. But there is only one method at order 3: RadaulIA.

### Optimization of (2,2)

best feasible point (0.749999939992 ; 0.250000060009 ; 0.33333280449 ; 0.999999998633 ; 0.416655823215 ; -0.0833225527662 ; 0.74999932909 ; 0.250000055725) cpu time used 0.3879s.

with a cost of  $[-\infty, 2.89787805696 \cdot 10^{-11}]$ : there is an order 3 !

#### Verification with solver

We add constraints  $b_1 = 0.75$  and  $c_2 = 1$ , then we find RadaullA

# Explicit 3 stages 3 order



### Theory (again)

There is countless explicit (3,3)-methods, but there is no order 4 method with 3 stages.

#### With optimizer: Erk33

[0, 0]	[0, 0]	[0, 0]	[0, 0]
0.4659048[706, 929]	0.4659048[706, 929]	[0, 0]	[0, 0]
0.8006855[74,83]	-0.154577[20, 17]	0.9552627[48, 86]	[0, 0]
	0.19590[599,600]	0.42961[399, 400]	0.3744800[0, 1]

#### Comparison to Kutta (known to be efficient)

Norm of order constraints at order 4:

- ERK33: 0.045221[277, 304]
- Kutta: 0.058925

 $\Rightarrow$  Our method is then closer to fourth order than Kutta.

Kutta third order:			
0	0	0	0
1/2	1/2	0	0
1	-1	2	0
	1/6	2/3	1/6

Constraint Programming and Runge-Kutta Experimentations

#### ENSTA ParisTech -Universite PARIS-SACLAY

### Integration with Erk33, on VanDerPol

Methods	time	nb of steps	norm of diameter of final solution
ERK33	3.7	647	$2.2 \cdot 10^{-5}$
Kutta (3,3)	3.55	663	$3.4 \cdot 10^{-5}$
RK4 (4,4)	4.3	280	$1.9\cdot10^{-5}$

 $\Rightarrow$  Equivalent to Kutta in term of time, but performance closer to RK4

### Linear Stability



Example of explicit methods (s=p) [Hairer]

$$R(z) = 1 + z \sum_{j} b_j + z^2 \sum_{j,k} b_j a_{jk} + z^3 \sum_{j,k,l} b_j a_{jk} a_{kl} + \dots$$

Stability domain given by  $S = \{z \in \mathcal{C} : |R(z)| \leq 1\}$ 

For RK4: 
$$R(z) = 1 + z + \frac{z^2}{2} + \frac{z^3}{6} + \frac{z^4}{24}$$

After z = x + iy, and some processing:

$$\begin{aligned} |R(x,y)| &= \sqrt{((((((((0.166667 * x^3) * y) + ((0.5 * x^2) * y)) - ((0.166667 * x) * y^3)) + ((1 * x) * y)) - (0.166667 * y^3)) + y)^2 + \\ (((((((((0.0416667 * x^4) + (0.166667 * x^3)) - ((0.25 * x^2) * y^2)) + (0.5 * x^2)) - ((0.5 * x) * y^2)) + x) + (0.0416667 * y^4)) - (0.5 * y^2)) + 1)^2)) \le 1 \end{aligned}$$

### Linear Stability





Paving of stability domain for RK4 method with high precision coefficients (blue) and with error  $(10^{-8} \text{ and } 10^{-2})$  on coefficients (red).

### Algebraically stable



Algebraically stable if:

- $b_i \geq 0$ , for all  $i = 1, \ldots, s$
- ▶  $M = (m_{ij}) = (b_i a_{ij} + b_j a_{ji} b_i b_j)_{i,j=1}^s$  is non-negative definite

#### Problem to solve

Solving the eigenvalue problem  $det(A - \lambda I) = 0$  (1) and proving  $\lambda > 0$ .

For 3-stage Runge-Kutta methods:  $(m_{11} - \lambda) * ((m_{22} - \lambda) * (m_{33} - \lambda) - m_{23} * m_{32}) - m_{12} * (m_{21} * (m_{33} - \lambda) - m_{23} * m_{31}) + m_{13} * (m_{21} * m_{32} - (m_{22} - \lambda) * m_{31}) = 0$ 

With contractor programming (Fwd/Bwd + Newton) Eq.(1) has no solution in  $] - \infty, 0[\equiv M$  is non-negative definite.

### Algebraically stable



### Verification of theory

- $\blacktriangleright$  Lobatto IIIC: contraction to empty set  $\Rightarrow$  algebraically stable
- ▶ Lobatto IIIA: solution found  $(-0.0481125) \Rightarrow$  not algebraically stable

#### With floating number

Lobatto IIIC with error of  $10^{-9}$  on  $a_{ij}$ : solution found  $(-1.03041 \cdot 10^{-05})$  $\Rightarrow$  not algebraically stable

### Algebraically stable



### Verification of theory

- $\blacktriangleright$  Lobatto IIIC: contraction to empty set  $\Rightarrow$  algebraically stable
- ▶ Lobatto IIIA: solution found  $(-0.0481125) \Rightarrow$  not algebraically stable

#### With floating number

Lobatto IIIC with error of  $10^{-9}$  on  $a_{ij}$ : solution found  $(-1.03041 \cdot 10^{-05})$  $\Rightarrow$  not algebraically stable

### Symplectic



Symplectic if 
$$M = 0$$
, with  $M = (m_{ij}) = (b_i a_{ij} + b_j a_{ji} - b_i b_j)_{i,j=1}^s$ 

#### Problem to solve

 $0 \in [M]$  with interval arithmetic

#### Verification of theory with Gauss-Legendre:

$$M = 10^{-17} \cdot \begin{pmatrix} [-1.38, 1.38] & [-2.77, 2.77] & [-2.77, 1.38] \\ [-2.77, 2.77] & [-2.77, 2.77] & [-1.38, 4.16] \\ [-2.77, 1.38] & [-1.38, 4.16] & [-1.38, 1.38] \end{pmatrix}$$

With  $a_{1,2} = 2.0/9.0 - \sqrt{15.0}/15.0$  computed with float

$$M = \begin{pmatrix} [-1.38e^{-17}, 1.38e^{-17}] & [-1.91e^{-09}, -1.91e^{-09}] & [-2.77e^{-17}, 1.38e^{-17}] \\ [-1.91e^{-09}, -1.91e^{-09}] & [-2.77e^{-17}, 2.77e^{-17}] & [-1.38e^{-17}, 4.16e^{-17}] \\ [-2.77e^{-17}, 1.38e^{-17}] & [-1.38e^{-17}, 4.16e^{-17}] & [-1.38e^{-17}, 1.38e^{-17}] \end{pmatrix}$$

### Symplectic



Symplectic if 
$$M = 0$$
, with  $M = (m_{ij}) = (b_i a_{ij} + b_j a_{ji} - b_i b_j)_{i,j=1}^s$ 

#### Problem to solve

 $0 \in [M]$  with interval arithmetic

Verification of theory with Gauss-Legendre:

$$M = 10^{-17} \cdot \begin{pmatrix} [-1.38, 1.38] & [-2.77, 2.77] & [-2.77, 1.38] \\ [-2.77, 2.77] & [-2.77, 2.77] & [-1.38, 4.16] \\ [-2.77, 1.38] & [-1.38, 4.16] & [-1.38, 1.38] \end{pmatrix}$$

With  $a_{1,2} = 2.0/9.0 - \sqrt{15.0}/15.0$  computed with float

$$M = \begin{pmatrix} [-1.38e^{-17}, 1.38e^{-17}] & [-1.91e^{-09}, -1.91e^{-09}] & [-2.77e^{-17}, 1.38e^{-17}] \\ [-1.91e^{-09}, -1.91e^{-09}] & [-2.77e^{-17}, 2.77e^{-17}] & [-1.38e^{-17}, 4.16e^{-17}] \\ [-2.77e^{-17}, 1.38e^{-17}] & [-1.38e^{-17}, 4.16e^{-17}] & [-1.38e^{-17}, 1.38e^{-17}] \end{pmatrix}$$

### Conclusion

#### Validated simulation with RK

- Method to bound the LTE
- Contractor based approach to solve Implicit RK
- Good results, even for stiff problems
- Library DynIbex (DAEs, constrained ODEs)

#### Constraint programming for RK

- Tool to re-discover the theory on RK methods...
- …and able to define new (optimal) schemes !

#### Future works

- Dynlbex in continuous development
- New RK schemes with higher order
- Solve some open problems



Conclusion



# Questions ?

Julien et Alexandre - Runge-Kutta

November 13, 2018- 46



# Appendices