

# Runge-Kutta guaranteed integration of ODEs

Olivier BOUISSOU

`olivier.bouissou@cea.fr`

CEA Saclay

Taylor Methods Workshop 2006  
Boca Raton, Florida

# Content of this talk.

- 1 Motivation
- 2 Taylor Series guaranteed integration
- 3 Guaranteed Runge Kutta method
- 4 Numerical results and Conclusion.

- 1 Motivation
- 2 Taylor Series guaranteed integration
- 3 Guaranteed Runge Kutta method
- 4 Numerical results and Conclusion.

*Context of this work:* Validation of embedded systems (avionics, automotive).

- Hybrid Systems: composed of two distinct parts
  - *discrete subsystem*: a discrete transition system (finite automata, C program).
  - *continuous subsystem*: a switched system of differential equations.
- Validation of such systems:
  - computes overapproximation of all reachable states.
  - needs rigorous bounds on the all the possible values of the continuous variables.

*Context of this work:* Validation of embedded systems (avionics, automotive).

- Hybrid Systems: composed of two distinct parts
  - *discrete subsystem*: a discrete transition system (finite automata, C program).
  - *continuous subsystem*: a switched system of differential equations.
- Validation of such systems:
  - computes overapproximation of all reachable states.
  - needs rigorous bounds on the all the possible values of the continuous variables.

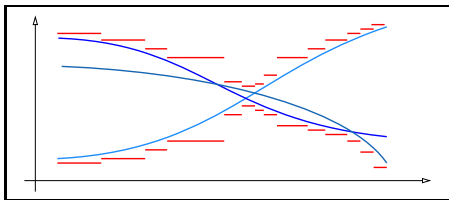
*What we need:* a method for computing representable functions which are guaranteed to enclose all the possible continuous dynamics.

# Objectives.

Suppose you have a switched dynamical system:

$$b \rightarrow (\dot{y} = f(y)) \square b' \rightarrow (\dot{y} = g(y))$$

We want to compute two functions that are guaranteed to enclose all the possible values of  $y$ .

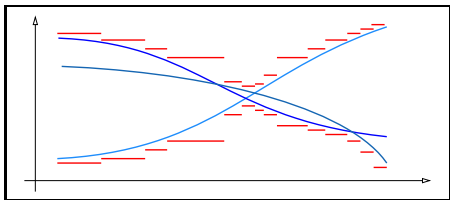


# Objectives.

Suppose you have a switched dynamical system:

$$b \rightarrow (\dot{y} = f(y)) \square b' \rightarrow (\dot{y} = g(y))$$

We want to compute two functions that are guaranteed to enclose all the possible values of  $y$ .



*What we really need:* given  $\dot{y} = f(y)$ , a set of enclosures  $[y_n]$  such that  $\forall t_n, y(t_n) \in [y_n]$ .

# What already exists.

- On the one side, validated integration using Taylor methods:
  - Taylor series expansion w.r.t. time only: AWA, VNODE
  - Taylor series expansion w.r.t. time and initial values: COSY VI
  - They mainly differ in the representation of the computed enclosures (intervals or Taylor models).
  
- On the other side, there are non validated integration methods:
  - Euler, Runge-Kutta, . . .
  - They have been intensively used for simulation and engineers often know how to tune them.



- 1 Motivation
- 2 Taylor Series guaranteed integration**
- 3 Guaranteed Runge Kutta method
- 4 Numerical results and Conclusion.

# Interval Taylor series methods

We start from the Interval Initial Value problem:

$$\dot{y} = f(y), \quad y(t_0) \in [y_0] \quad (3.1)$$

- The goal of the integration is to compute a sequence of interval enclosures  $[y_j]$  such that  $y(t_j) \in [y_j]$ .

We start from the real valued Taylor series expansion:

$$y_{j+1} = y_j + \sum_{k=1}^{N-1} f^{[k-1]}(y_j) h_j^k + h_j^N f^{[N-1]}(y(x_s))$$

# Interval Taylor series methods

We start from the Interval Initial Value problem:

$$\dot{y} = f(y), \quad y(t_0) \in [y_0] \quad (3.1)$$

- The goal of the integration is to compute a sequence of interval enclosures  $[y_j]$  such that  $y(t_j) \in [y_j]$ .

We start from the real valued Taylor series expansion:

$$y_{j+1} = y_j + \sum_{k=1}^{N-1} f^{[k-1]}(y_j) h_j^k + h_j^N f^{[N-1]}(y(x_s))$$

A naive transformation of this formula into interval arithmetics gives:

$$[y_{j+1}] = [y_j] + \sum_{k=1}^{N-1} f^{[k-1]}([y_j]) h_j^k + h_j^N f^{[N-1]}([\tilde{y}_j])$$

- *Computation of  $[\tilde{y}_j]$* : Picard-Lindelöf operator (or higher order methods).
- *Avoiding  $[y_j]$  to grow*: we compute the interval evaluations with the mean value form:

$$\begin{aligned} [y_{j+1}] &= \hat{y}_j + \sum_{k=1}^{N-1} f^{[k-1]}(\hat{y}_j) h_j^k + h_j^N f^{[N-1]}([\tilde{y}_j]) + \\ &\quad \left( I + \sum_{k=1}^{N-1} J(f^{[k-1]}, [y_j]) h_j^k \right) ([y_j] - \hat{y}_j) \\ &= y_{j+1} + h_j^N f^{[N-1]}([\tilde{y}_j]) + S_j \cdot ([y_j] - \hat{y}_j) \end{aligned}$$

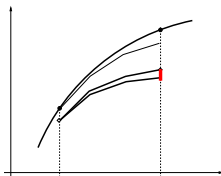
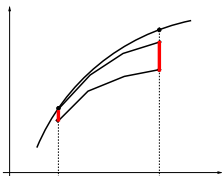
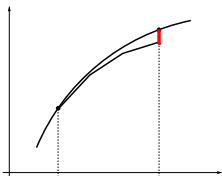
So, the enclosure at the next step is computed as the sum of :

- a point:  $y_{j+1} = \hat{y}_j + \sum_{k=1}^{N-1} f^{[k-1]}(\hat{y}_j) h_j^k$
- a local error term:  $h_j^N f^{[N-1]}([\tilde{y}_j])$
- an error propagation term:  $S_j.([y_j] - \hat{y}_j)$

Wrapping effect occurs during the computation of the error propagation. To reduce it, you can use for example the **QR-factorization** method.

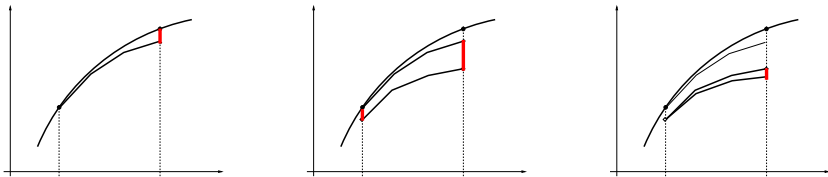
# Our Method.

- *Compute the point approximation and the error independently.*
  - not validated approximation points are computed without any interval arithmetics.
  - errors are computed in a second time and compared to a user defined tolerance  $\epsilon$ .
- The global error may be divided into three parts:
- Each error is computed independently:



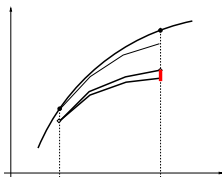
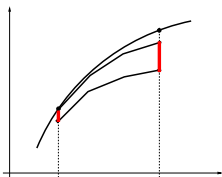
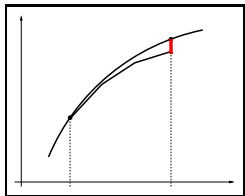
# Our Method.

- Compute the point approximation and the error independently.
- *The global error may be divided into three parts:*
  - approximation error due to limitations of the method.
  - propagation of the previous error.
  - roundoff error due to machine finite precision.
- Each error is computed independently:



# Our Method.

- Compute the point approximation and the error independently.
- The global error may be divided into three parts:
  - approximation error due to limitations of the method.
  - propagation of the previous error.
  - roundoff error due to machine finite precision.
- *Each error is computed independently:*

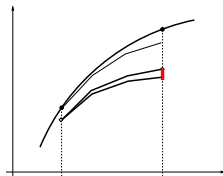
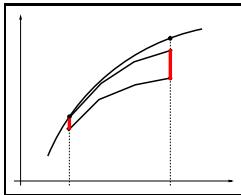
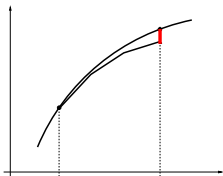


Picard-Lindelöf operator for method error.



# Our Method.

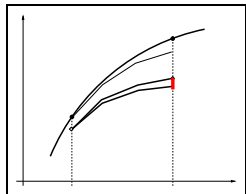
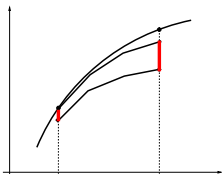
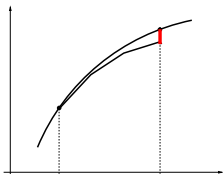
- Compute the point approximation and the error independently.
- The global error may be divided into three parts:
  - approximation error due to limitations of the method.
  - propagation of the previous error.
  - roundoff error due to machine finite precision.
- *Each error is computed independently:*



Löhner's factorization method for the propagation.

# Our Method.

- Compute the point approximation and the error independently.
- The global error may be divided into three parts:
  - approximation error due to limitations of the method.
  - propagation of the previous error.
  - roundoff error due to machine finite precision.
- *Each error is computed independently:*



Global error arithmetics for the roundoff error.

# Notations.

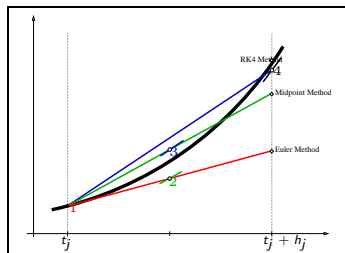
- Real numbers:  $a \in \mathbb{R}$
- Floating point numbers:  $\mathbf{a} \in \mathbb{F}$
- Intervals:  $[a] = [\underline{a}, \bar{a}]$
- Floating point intervals:  $\mathbf{[a]} = [\underline{\mathbf{a}}, \bar{\mathbf{a}}]$
- Initial value problem:

$$\dot{y} = f(y), \quad y(t_0) \in y_0 + [e_0] \quad \text{with} \quad \begin{cases} y : \mathbb{R} \rightarrow \mathbb{R}^d \\ f : \mathbb{R}^d \rightarrow \mathbb{R}^d \end{cases} \quad (3.2)$$

- 1 Motivation
- 2 Taylor Series guaranteed integration
- 3 Guatanteed Runge Kutta method**
- 4 Numerical results and Conclusion.

# The RK4 Method.

- Iterative method for computing approximation points of the solution of (3.2)
- Order 4 method, with adaptative step size control.
- Needs four evaluations of  $f$  for computing  $y_{j+1}$  out of  $y_j$ .

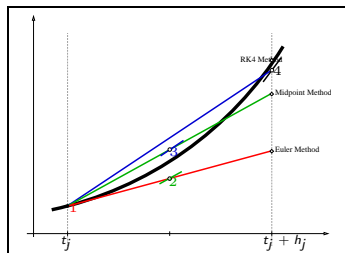


$$\begin{aligned}k_1 &= f(y_j) \\k_2 &= f(y_j + h/2 \cdot k_1) \\k_3 &= f(y_j + h/2 \cdot k_2) \\k_4 &= f(y_j + h \cdot k_3) \\y_{j+1} &= y_j + \frac{h}{6} (k_1 + 2k_2 + 2k_3 + k_4)\end{aligned}$$

- The iteration of the scheme gives  $(\mathbf{y}_n)_{n \in \mathbb{N}}$

# The RK4 Method.

- Iterative method for computing approximation points of the solution of (3.2)
- Order 4 method, with adaptative step size control.
- Needs four evaluations of  $f$  for computing  $y_{j+1}$  out of  $y_j$ .



$$\begin{aligned}k_1 &= f(y_j) \\k_2 &= f(y_j + h/2 \cdot k_1) \\k_3 &= f(y_j + h/2 \cdot k_2) \\k_4 &= f(y_j + h \cdot k_3) \\y_{j+1} &= y_j + \frac{h}{6} (k_1 + 2k_2 + 2k_3 + k_4)\end{aligned}$$

- The iteration of the scheme gives  $(\mathbf{y}_n)_{n \in \mathbb{N}}$

Goal: Find an enclosure of  $y(t_j) - \mathbf{y}_j$ .

# Some definitions.

We define the following functions:

$$k_1(y, h) = f(y)$$

$$k_2(y, h) = f(y + h/2 \cdot k_1(y, h))$$

$$k_3(y, h) = f(y + h/2 \cdot k_2(y, h))$$

$$k_4(y, h) = f(y + h k_3(y, h))$$

$$\Phi(y, h) = y + \frac{h}{6} (k_1(y, h) + 2k_2(y, h) + 2k_3(y, h) + k_4(y, h))$$

We then have:

$$y_{j+1} = \Phi(y_j, h_j)$$

We also define:

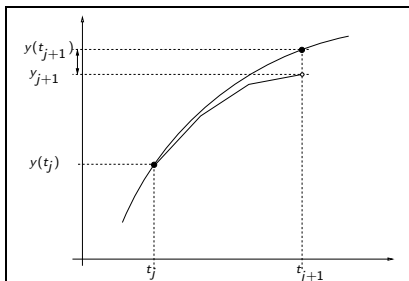
$$\varphi_j : t \mapsto \Phi(t - t_j, y(t_j)) \quad \psi_j : y \mapsto \Phi(h_j, y)$$

# Computing the error: one step error



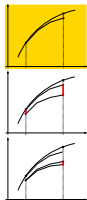
- Let us suppose that  $y_j = y(t_j)$ .
  - $y_{j+1} = \varphi_j(t_{j+1})$
  - $\forall i \in [0, 4], \frac{d^i y}{dt^i}(t_j) = \frac{d^i \varphi_j}{dt^i}(t_j)$
  - Therefore, there exists  $\xi \in [t_j, t_{j+1}]$  such that

$$y(t_{j+1}) - \varphi_j(t_{j+1}) = h_j^5 (y - \varphi_j)^{[5]}(\xi)$$



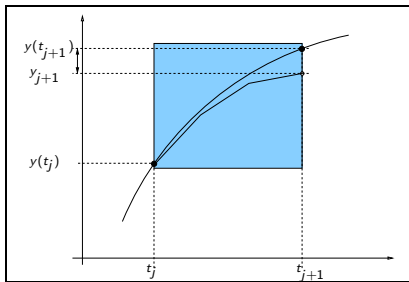


# Computing the error: one step error



- Let us suppose that  $y_j = y(t_j)$ .
  - $y_{j+1} = \varphi_j(t_{j+1})$
  - $\forall i \in [0, 4], \frac{d^i y}{dt^i}(t_j) = \frac{d^i \varphi_j}{dt^i}(t_j)$
  - Therefore, there exists  $\xi \in [t_j, t_{j+1}]$  such that

$$y(t_{j+1}) - \varphi_j(t_{j+1}) = h_j^5 (y - \varphi_j)^{[5]}(\xi)$$



## Computing the error: one step error (2)



- We compute an a priori enclosure  $[\tilde{y}_j]$  such that:

$$\forall t \in [t_j, t_{j+1}], y(t) \in [\tilde{y}_j]$$

- Picard-Lindelöf operator  $P(R) = y_j + [0, h_j].f(R)$  or higher order methods.
  - Then, we have:

$$y(t_{j+1}) - \varphi_j(t_{j+1}) \in \frac{h_j^5}{120} \left( \frac{d^4 f}{dx^4}([\tilde{y}_j]) - \frac{d^5 \varphi_j}{dx^5}([t_j, t_{j+1}]) \right)$$

# Computing the error: one step error (2)



- We compute an a priori enclosure  $[\tilde{y}_j]$  such that:

$$\forall t \in [t_j, t_{j+1}], y(t) \in [\tilde{y}_j]$$

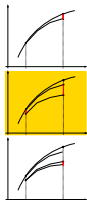
- Picard-Lindelöf operator  $P(R) = y_j + [0, h_j].f(R)$  or higher order methods.
  - Then, we have:

$$y(t_{j+1}) - \varphi_j(t_{j+1}) \in \frac{h_j^5}{120} \left( \frac{d^4 f}{dx^4}([\tilde{y}_j]) - \frac{d^5 \varphi_j}{dx^5}([t_j, t_{j+1}]) \right)$$

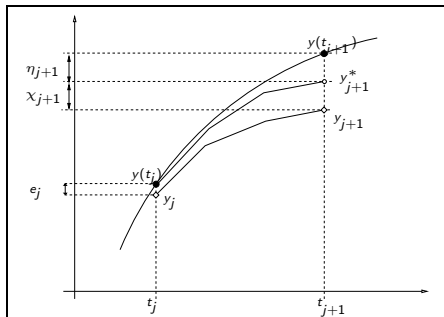
- In Taylor series method, the local error is:

$$\frac{h_j^N}{N!} \frac{d^{N-1} f}{dx^{N-1}}([\tilde{y}_j])$$

# Computing the error: propagation



Now, what if there were an error:  $y(t_j) \in y_j + [e_j]$



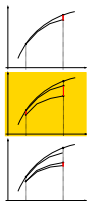
- We now have:  $y_{j+1} = \psi_j(y_j)$  and  $y_{j+1}^* = \psi_j(y(t_j))$
- So,  $y_{j+1} - y_{j+1}^* = \text{Jac}(\psi_j, \chi_j) \cdot e_j$  with  $\chi_j \in [y_j, y(t_j)]$



- This is overapproximated with interval arithmetic:

$$y_{j+1} - y_{j+1}^* \in \text{Jac}(\psi_j, y_j + [e_j]) \cdot [\epsilon_j]$$

# Computing the error: propagation



- This is overapproximated with interval arithmetic:

$$y_{j+1} - y_{j+1}^* \in \text{Jac}(\psi_j, y_j + [e_j]) \cdot [e_j]$$

- In Taylor series method, the propagation of the previous error is given by:

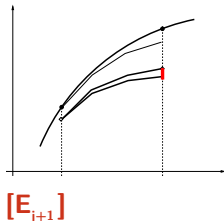
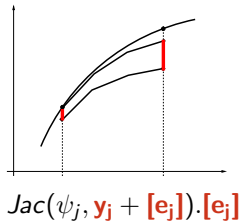
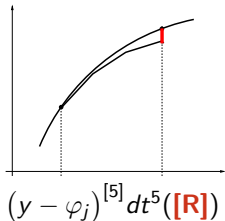
$$\left( I + \sum_{k=1}^{N-1} J(f^{[k-1]}, [y_j]) h_j^k \right) ([y_j] - \hat{y}_j)$$

- In both cases, the use of the QR preconditioning keeps the method stable.

# To sum up.

Goal: give a rigorous bound on  $y(t_j) - \mathbf{y}_j$

$$\begin{aligned}y(t_{j+1}) &= \mathbf{y}_{j+1} + (y(t_{j+1}) - y_{j+1}^*) + (y_{j+1}^* - \mathbf{y}_{j+1}) \\ &= \mathbf{y}_{j+1} + (y - \varphi_j)^{[5]}(\xi) + (y_{j+1}^* - y_{j+1}) - E_{j+1} \\ [\mathbf{e}_{j+1}] &\in (y - \varphi_j)^{[5]}([\mathbf{R}]) + \text{Jac}(\psi_j, \mathbf{y}_j + [\mathbf{e}_j]) \cdot [\mathbf{e}_j] - [E_{j+1}]\end{aligned}$$



# To sum up.

**Goal:** give a rigorous bound on  $y(t_j) - \mathbf{y}_j$

$$\begin{aligned}y(t_{j+1}) &= \mathbf{y}_{j+1} + (y(t_{j+1}) - y_{j+1}^*) + (y_{j+1}^* - \mathbf{y}_{j+1}) \\ &= \mathbf{y}_{j+1} + (y - \varphi_j)^{[5]}(\xi) + (y_{j+1}^* - y_{j+1}) - E_{j+1} \\ \mathbf{[e}_{j+1}] &\in (y - \varphi_j)^{[5]}(\mathbf{[R]}) + \text{Jac}(\psi_j, \mathbf{y}_j + \mathbf{[e}_j]) \cdot \mathbf{[e}_j] - \mathbf{[E}_{j+1}]\end{aligned}$$

- Implementation issues:
  - Löhner's QR-factorization method for reducing the wrapping effect
  - Overapproximation of  $\mathbf{[E}_j]$ : we use the *global error arithmetics*



# Computing the error : round-off error.



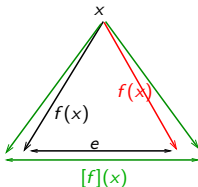
$$a = f_a + e_a \vec{\varepsilon}_e \quad \text{and} \quad b = f_b + e_b \vec{\varepsilon}_e$$

$$a + b = \uparrow_{\sim} (f_a + f_b) + (e_a + e_b + \downarrow_{\sim} (f_a + f_b)) \vec{\varepsilon}_e$$

$$a - b = \uparrow_{\sim} (f_a - f_b) + (e_a - e_b + \downarrow_{\sim} (f_a - f_b)) \vec{\varepsilon}_e$$

$$a \times b = \uparrow_{\sim} (f_a \times f_b) + (e_a f_b + e_b f_a + e_a e_b + \downarrow_{\sim} (f_a \times f_b)) \vec{\varepsilon}_e$$

- Let the user know both the result ( $f$ ) and its distance to the real result.



# Computing the error : round-off error.



Suppose that we are working on a 4 digits machine. We have two global error numbers,  $a = 621.3 + 0.05\overrightarrow{\varepsilon}_e$  and  $b = 1.287 + 0.0005\overrightarrow{\varepsilon}_e$ , that we want to multiply.

$$\begin{array}{rcll}
 & 621.3 & + & 0.05\overrightarrow{\varepsilon}_e & a \\
 \times & 1.287 & + & 0.0005\overrightarrow{\varepsilon}_e & b \\
 \hline
 = & 799.6131 & & & \text{Real result} \\
 & & + & 0.06435\overrightarrow{\varepsilon}_e & \text{Error due to } a \\
 & & + & 0.31065\overrightarrow{\varepsilon}_e & \text{Error due to } b \\
 & & + & 0.000025\overrightarrow{\varepsilon}_e & \text{Second order term} \\
 \hline
 = & 799.6\varepsilon & & & \text{Floating point result} \\
 & & & & = \uparrow_{\sim} (f_a \times f_b) \\
 & & + & 0.375025\overrightarrow{\varepsilon}_e & \\
 & & + & 0.0131\overrightarrow{\varepsilon}_e & \downarrow_{\sim} (f_a \times f_b) \\
 \hline
 = & 799.6\varepsilon & + & 0.388[1, 2]\overrightarrow{\varepsilon}_e & 
 \end{array}$$

- 1 Motivation
- 2 Taylor Series guaranteed integration
- 3 Guaranteed Runge Kutta method
- 4 Numerical results and Conclusion.**

# Numerical Results.

- The method has been implemented in a library GRKlib:
  - use formal derivation techniques for computing the derivatives.
  - propagates separately method and round off errors.
  - can be used with both double and multiprecision arithmetics.
  - only implements order 4 Runge-Kutta formula.
- Tried it on various problems:
  -

# Numerical Results.

- The method has been implemented in a library GRKlib:
  - use formal derivation techniques for computing the derivatives.
  - propagates separately method and round off errors.
  - can be used with both double and multiprecision arithmetics.
  - only implements order 4 Runge-Kutta formula.
- Tried it on various problems:
  - Linear problem  
Simple rotation:

$$\dot{Y} = \begin{pmatrix} 0 & -0.707107 & -0.5 \\ 0.707107 & 0 & 0.5 \\ 0.5 & 0 & -0.5 \end{pmatrix} Y$$

$t =$	100	500	1000
$\epsilon$	$4 \cdot 10^{-4}$	$2 \cdot 10^{-3}$	$4 \cdot 10^{-3}$

# Numerical Results.

- The method has been implemented in a library GRKlib:
  - use formal derivation techniques for computing the derivatives.
  - propagates separately method and round off errors.
  - can be used with both double and multiprecision arithmetics.
  - only implements order 4 Runge-Kutta formula.
- Tried it on various problems:
  - Linear problem  
Simple contraction:

$$\dot{Y} = \begin{pmatrix} -0.4375 & 0.0625 & -0.265165 \\ 0.0625 & -0.4375 & -0.265165 \\ -0.265165 & -0.265165 & -0.375 \end{pmatrix} Y$$

$t =$	100	500	1000
$\epsilon$	$3 \cdot 10^{-5}$	$3 \cdot 10^{-5}$	$3, 3 \cdot 10^{-5}$

# Numerical Results.

- The method has been implemented in a library GRKlib:
  - use formal derivation techniques for computing the derivatives.
  - propagates separately method and round off errors.
  - can be used with both double and multiprecision arithmetics.
  - only implements order 4 Runge-Kutta formula.
- Tried it on various problems:
  - Non linear problem  
Lorenz equations:

$$\begin{cases} \dot{y}_1 = 10(y_2 - y_1) \\ \dot{y}_2 = y_1(28 - y_3) - y_2 \\ \dot{y}_3 = y_1 * y_2 - \frac{8}{3}y_3 \end{cases}$$

$t =$	5	10	15
$\epsilon$	$2.10^{-8}$	$4.10^{-5}$	$6.10^{-4}$

# Conclusion.

In this talk, we:

- showed how to make a validated integration method out of a Runge-Kutta integration scheme.
- informally compared the formulae for the error with the ones from Taylor series method.

Our implementation shows that we can achieve good precision results, although only order 4 method is used.



# Conclusion.

In this talk, we:

- showed how to make a validated integration method out of a Runge-Kutta integration scheme.
- informally compared the formulae for the error with the ones from Taylor series method.

Our implementation shows that we can achieve good precision results, although only order 4 method is used.

- Advantage of the method:
  - based on well known numerical method (Runge-Kutta), which can be finely tuned for every problem.
  - it allows effective step size control, with ideas coming from control theory.

# Conclusion.

In this talk, we:

- showed how to make a validated integration method out of a Runge-Kutta integration scheme.
- informally compared the formulae for the error with the ones from Taylor series method.

Our implementation shows that we can achieve good precision results, although only order 4 method is used.

- Advantage of the method:
  - based on well known numerical method (Runge-Kutta), which can be finely tuned for every problem.
  - it allows effective step size control, with ideas coming from control theory.
- Further work:
  - add other integration schemes to our library (order 5/6 RK methods).
  - use better domains for the representation of the error to reduce wrapping effect (Taylor models).