

# Rien Quirynen

## ACADO Code Generation tool

## including material from B. Houska and M. Vukov

TEMPO Spring School on NMPC

University of Freiburg



– Katholieke Universiteit Leuven





- 3 Real-Time Iterations
- Application examples



## Outline



- 2 Automatic Code Generation
- 3 Real-Time Iterations
- Application examples



### Introduction

## Nonlinear Dynamic Systems



# **Optimal Control**

#### Many Fields of Application:

- Optimal Motions in Robotics
- Operation of a Chemical Plant
- Seasonal Heat Storage
- Kite Power

#### **Problems:**

- Optimize Parameters/Controls
- Uncertainties/Disturbances







# www.acadotoolkit.org

Key Properties of ACADO Toolkit [Houska et al 2009]

- Open Source (LGPL)
- Automatic Control And Dynamic Optimization
- User friendly interface close to mathematical syntax

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#### Multiplatform support

- C++: Linux, OS X, Windows
- MATLAB

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#### List of Developers:





Moritz Diehl Scientific advisor

Hans Joachim Ferreau Main developer



Boris Houska Main developer



**Filip Logist** Multi-objective optimization



**Rien Ouirvnen** Code generation



Dries Telen Optimal Experimental Design



Mattia Valerio Multi-objective optimal control



Milan Vukov Code generation for MPC & MHE

ACADO toolkit

## Tutorial Example: Time Optimal Control of a Rocket

Mathematical Formulation:

 $\min_{s(\cdot),v(\cdot),m(\cdot),u(\cdot),T} T$ 

subject to

$$\begin{array}{rcl} \dot{s}(t) &=& v(t) \\ \dot{v}(t) &=& \frac{u(t)-0.2 \, v(t)^2}{m(t)} \\ \dot{m}(t) &=& -0.01 \, u(t)^2 \\ s(0) &=& 0 \quad s(T) \,=& 10 \\ v(0) &=& 0 \quad v(T) \,=& 0 \\ m(0) &=& 1 \\ \hline -0.1 &\leq& v(t) \,\leq& 1.7 \\ -1.1 &\leq& u(t) \,\leq& 1.1 \\ 5 &\leq& T \quad\leq& 15 \end{array}$$

#### ACADO toolkit

## Tutorial Example: Time Optimal Control of a Rocket

Mathematical Formulation:

 $\begin{array}{l} \text{minimize} \\ s(\cdot), v(\cdot), m(\cdot), u(\cdot), T \end{array} T$ 

subject to

$\dot{s}(t)$	=	v(t)
$\dot{v}(t)$	=	$\frac{u(t)-0.2 v(t)^2}{m(t)}$
ṁ(t)	=	$-0.01 u(t)^2$
s(0) v(0) m(0)	= 0 = 0 = 1	s(T) = 10  v(T) = 0  l
$-0.1 \\ -1.1$	$\leq$	$v(t) \leq 1.7$ u(t) < 1.1

- 1.1	$\geq$	$u(\iota)$	$\geq$	T.T
5	$\leq$	Т	$\leq$	15

DifferentialState s,v,m	1;
Control	ι;
Parameter 1	1;
DifferentialEquation f( 0.0, T )	;
OCP ocp( 0.0, T );	
<pre>ocp.minimizeMayerTerm( T );</pre>	
f << dot(s) == v;	
f << dot(v) == (u-0.2*v*v)/m;	
f << dot(m) == -0.01*u*u;	
ocp.subjectTo( f )	;
ocp.subjectTo( AT_START, s == 0.0 )	;
ocp.subjectTo( AT_START, v == 0.0 )	;
ocp.subjectTo( AT_START, m == 1.0 )	;
ocp.subjectTo( AT_END , s == 10.0 )	;
ocp.subjectTo( AT_END , v == 0.0 )	;

ocp.subjectTo( -0.1 <= v <= 1.7 ); ocp.subjectTo( -1.1 <= u <= 1.1 ); ocp.subjectTo( 5.0 <= T <= 15.0 ); OptimizationAlgorithm algorithm(ocp); algorithm.solve();

## ACADO toolkit

## Optimization Results



# • Optimal control of dynamic systems (ODE, DAE)

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- Multi-objective optimization (joint work with Filip Logist)

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# $\rightarrow$ "standard" ACADO Toolkit

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- Real-Time MPC and Code Export

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- Robust optimal control
- Real-Time MPC and Code Export
  - $\rightarrow$  "ACADO Code Generation"

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# ACADO Toolkit

Software and algorithms for ...

- Dynamic optimization
- code generation tool
- Fast NMPC and MHE
- MATLAB interface



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Software and algorithms for ...

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Why code generation?

## optimization:

- eliminate computations
- known dimensions and sparsity patterns
- no dynamic memory
- code reorganization, ...
- Customization: precision, language, libraries, ...



# ACADO Toolkit

Software and algorithms for ...



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• parametric: initial condition

$$\min_{x(\cdot),u(\cdot)} \quad \int_0^T \|F(t, x(t), u(t)) - \bar{y}(t)\|_2^2 dt \text{ s.t. } \quad x(0) = \bar{x}_0 \quad \dot{x}(t) = f(t, x(t), u(t)) \quad 0 \geq h(x(t), u(t)) \quad 0 \geq r(x(0), x(T)) \quad \forall t \in [0, T]$$

- parametric: initial condition
- tracking MPC

$$\min_{x(\cdot),u(\cdot)} \int_{0}^{T} \|F(t,x(t),u(t)) - \bar{y}(t)\|_{2}^{2} dt$$
s.t.  $x(0) = \bar{x}_{0}$ 
 $\dot{x}(t) = f(t,x(t),u(t))$ 
 $0 \ge h(x(t),u(t))$ 
 $0 \ge r(x(0),x(T))$ 
 $\forall t \in [0,T]$ 

- parametric: initial condition
- tracking MPC
- nonlinear model

Tracking MPC

Economic MPC

$$\min_{x(\cdot),u(\cdot)} \quad \int_{0}^{T} \|F(t,x(t),u(t)) - \bar{y}(t)\|_{2}^{2} dt$$
  
s.t.  $x(0) = \bar{x}_{0}$   
 $\dot{x}(t) = f(t,x(t),u(t))$   
 $0 \geq h(x(t),u(t))$   
 $0 \geq r(x(0),x(T))$   
 $\forall t \in [0,T]$ 

$$\min_{x(\cdot),u(\cdot)} \int_0^T l(t,x(t),u(t)) dt$$
s.t.  $x(0) = \bar{x}_0$ 
 $\dot{x}(t) = f(t,x(t),u(t))$ 
 $0 \ge h(x(t),u(t))$ 
 $0 \ge r(x(0),x(T))$ 
 $\forall t \in [0,T]$ 

T

Tracking MPC: continuous

$$\min_{x(\cdot),u(\cdot)} \quad \int_{0}^{T} \|F(t,x(t),u(t)) - \bar{y}(t)\|_{2}^{2} dt \text{ s.t. } x(0) = \bar{x}_{0} \dot{x}(t) = f(t,x(t),u(t)) 0 \geq h(x(t),u(t)) 0 \geq r(x(0),x(T)) \forall t \in [0,T]$$

Tracking MPC: continuous

ightarrow shooting discretization

$$\min_{x(\cdot),u(\cdot)} \quad \int_{0}^{T} \|F(t,x(t),u(t)) - \bar{y}(t)\|_{2}^{2} dt \quad \min_{x,t} \\ \text{s.t.} \quad x(0) = \bar{x}_{0} \qquad \qquad \text{s.t} \\ \dot{x}(t) = f(t,x(t),u(t)) \\ 0 \geq h(x(t),u(t)) \\ 0 \geq r(x(0),x(T)) \\ \forall t \in [0,T]$$

$$\min_{x,u} \qquad \sum_{i=0}^{N-1} \|F_i(x_i, u_i) - \bar{y}_i\|_2^2 + \|F_N(x_N)\|_2^2$$
s.t. 
$$0 = x_0 - \bar{x}_0$$

$$0 = x_{i+1} - \Phi_i(x_i, u_i)$$

$$0 \ge h_i(x_i, u_i)$$

$$0 \ge r(x_0, x_N)$$

$$\forall i = 0, \dots, N-1$$

#### Task of the integrator in RTI

- $x_{k+1} = \Phi_k(x_k, u_k)$
- nonlinear equality constraint



#### Task of the integrator in RTI

• 
$$x_{k+1} = \Phi_k(x_k, u_k)$$

• nonlinear equality constraint  $\downarrow$ 

$$ullet$$
 linearization at  $ar w_k=(ar x_k,ar u_k)$ 



$$0 = \mathbf{\Phi}_{\mathbf{k}}(\bar{\mathbf{w}}_{\mathbf{k}}) - x_{k+1} + \frac{\partial \mathbf{\Phi}_{\mathbf{k}}}{\partial \mathbf{w}}(\bar{\mathbf{w}}_{\mathbf{k}})(w_k - \bar{w}_k)$$

 integration and sensitivity generation is typically a major computational step

#### The 3-stage model structure



$$\begin{array}{ll} \underset{X,U}{\text{minimize}} & \sum_{i=0}^{N-1} \|F_i(x_i, u_i) - \bar{y}_i\|_2^2 + \|F_N(x_N)\|_2^2 \\ \text{subject to} & G_{eq}(\cdot) = \begin{bmatrix} x_0 - \bar{x}_0 \\ x_1 - \phi_0(x_0, u_0) \\ \vdots \end{bmatrix} = 0 \\ G_{ineq}(\cdot) = \begin{bmatrix} h_0(x_0, u_0) \\ \vdots \\ r(x_0, x_N) \end{bmatrix} \leq 0 \end{array}$$

$$\begin{split} \underset{X, U}{\text{minimize}} & \Phi_{\text{quad}}(X, U; X^{[k]}, U^{[k]}, Y^{[k]}, \lambda^{[k]}) \\ \text{subject to} & G_{\text{eq,lin}}(\cdot) = \begin{bmatrix} x_0 - \bar{x}_0 \\ x_1 - \phi_0(x_0^{[k]}u_0^{[k]}) - \begin{bmatrix} A_0^{[k]}, B_0^{[k]} \end{bmatrix} \begin{bmatrix} x_0 - x_0^{[k]} \\ u_0 - u_0^{[k]} \end{bmatrix} \end{bmatrix} = 0 \\ & \vdots \end{bmatrix} \\ G_{\text{ineq,lin}}(\cdot) = \begin{bmatrix} h_0(x_0^{[k]}u_0^{[k]}) + \begin{bmatrix} C_0^{[k]}, D_0^{[k]} \end{bmatrix} \begin{bmatrix} x_0 - x_0^{[k]} \\ u_0 - u_0^{[k]} \end{bmatrix} \\ & \vdots \\ r(\bar{x}_0, x_N^{[k]}) + C_N^{[k]}(x_N - x_N^{[k]}) \end{bmatrix} \le 0 \end{split}$$

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#### Objective quadratic subproblem

- Gauss-Newton: easy, convex, fast
- Exact Hessian:  $B_k = \nabla^2_W \mathcal{L}(\cdot)$

#### How to solve the structured convex QP?

$$\min_{\Delta X, \Delta U} \sum_{i=0}^{N-1} \begin{bmatrix} \Delta x_i \\ \Delta u_i \end{bmatrix}^\top \begin{bmatrix} Q_i & S_i \\ S_i^\top & R_i \end{bmatrix} \begin{bmatrix} \Delta x_i \\ \Delta u_i \end{bmatrix} + \begin{bmatrix} \Delta x_i \\ \Delta u_i \end{bmatrix}^\top \begin{bmatrix} q_i \\ r_i \end{bmatrix} + x_N^\top Q_N x_N + x_N^\top q_N$$

s.t. 
$$G_{\rm eq,lin}(\cdot) = \begin{bmatrix} \Delta x_0 - d_0 \\ \Delta x_1 - d_1 - [A_0, B_0] \begin{bmatrix} \Delta x_0 \\ \Delta u_0 \end{bmatrix} \end{bmatrix} = 0$$
  
 $\vdots$   
 $G_{\rm ineq,lin}(\cdot) = \begin{bmatrix} c_0 + [C_0, D_0] \begin{bmatrix} \Delta x_0 \\ \Delta u_0 \end{bmatrix} \\ \vdots \\ c_N + C_N \Delta x_N \end{bmatrix} \le 0$ 

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s.t. 
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structure exploiting, embedded convex solvers: *FORCES, qpDUNES, HPMPC, ...* 

#### Real-Time Iterations

#### How to solve the structured convex QP?

structure exploiting, embedded convex solvers: **OR** condensing,  $O(N^2)$  complexity

 $\begin{array}{ll} \underset{x_{0},u_{0},\ldots,x_{N}}{\minimize} & \frac{1}{2} \sum_{k=0}^{N-1} \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix}^{T} \begin{bmatrix} Q_{k} & S_{k} \\ S_{k}^{T} & R_{k} \end{bmatrix} \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix}^{L} + \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix}^{T} \begin{bmatrix} g_{k}^{*} \\ g_{k}^{*} \end{bmatrix}^{T} \\ & + \frac{1}{2} x_{N}^{T} Q_{e} x_{N} + x_{N}^{T} g_{e}^{*} \\ & + \frac{1}{2} x_{N}^{T} Q_{e} x_{N} + x_{N}^{T} g_{e}^{*} \\ & x_{k+1} = A_{k} x_{k} + B_{k} u_{k} + c_{k}, \text{ for } k = 0, \dots, N-1 \\ & x_{k}^{\text{lo}} \leq x_{k} \leq x_{k}^{\text{up}}, & \text{ for } k = 0, \dots, N-1 \\ & u_{k}^{\text{lo}} \leq u_{k} \leq u_{k}^{\text{up}}, & \text{ for } k = 0, \dots, N-1 \\ & b_{k}^{\text{lo}} \leq C_{k} x_{k} + D_{k} u_{k} \leq b_{k}^{\text{up}}, & \text{ for } k = 0, \dots, N-1 \\ & b_{e}^{\text{lo}} \leq C_{e} x_{N} \leq b_{e}^{\text{up}}, \end{array} \right)$ 





#### Real-Time Iterations

#### How to solve the structured convex QP?

structure exploiting, embedded convex solvers: **OR** condensing,  $O(N^2)$  complexity

$$\begin{array}{ll} \underset{x_{0},u_{0},\ldots,x_{N}}{\text{minimize}} & \frac{1}{2}\sum_{k=0}^{N-1} \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix}^{T} \begin{bmatrix} Q_{k} & S_{k} \\ S_{k}^{T} & R_{k} \end{bmatrix} \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix}^{+} \begin{bmatrix} y_{k} \\ y_{k} \end{bmatrix}^{T} \begin{bmatrix} g_{k} \\ g_{k}^{T} \end{bmatrix}^{T} \\ & + \frac{1}{2}x_{N}^{T}Q_{e}x_{N} + x_{N}^{T}g_{e}^{X} \\ & + \frac{1}{2}x_{N}^{T}Q_{e}x_{N} + x_{N}^{T}g_{e}^{X} \\ & x_{k+1} = A_{k}x_{k} + B_{k}u_{k} + c_{k}, \text{ for } k = 0, \dots, N-1 \\ & x_{k}^{lo} \leq x_{k} \leq x_{k}^{up}, & \text{for } k = 0, \dots, N-1, \\ & b_{C}^{lo} \leq L_{k}x_{k} + D_{k}u_{k} \leq b_{k}^{up}, & \text{for } k = 0, \dots, N-1, \\ & b_{C}^{lo} \leq C_{k}x_{k} + D_{k}u_{k} \leq b_{k}^{up}, & \text{for } k = 0, \dots, N-1, \\ & b_{C}^{lo} \leq C_{e}x_{N} \leq b_{e}^{up}, \end{array}$$



 $\longrightarrow$  solve the condensed QP with a dense linear algebra QP solver, e.g. <code>qpOASES</code>, www.qpoases.org

#### The RTI workflow for fast NMPC









#### Real-Time Iterations



#### Real-Time Iterations



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## 5 ACADO demo

## ERC HIGHWIND project <sup>1</sup>

MHE and NMPC implementation on an experimental test set-up for launch/recovery of an airborne wind energy (AWE) system [Geebelen, 2013], located at KU Leuven (new carousel in Freiburg).



<sup>&</sup>lt;sup>1</sup>Joint work: A. Wagner, M. Vukov, M. Zanon, K. Geebelen

## ERC HIGHWIND project

#### Problem specific info

- Nonlinear dynamics: 22 states and 3 inputs
- Nonlinear measurement functions (for camera and IMU)
- Sensors:
  - Camera measurements 12 data @ 10 Hz with delay
  - IMU measurements 6 data @ 500 Hz
  - $\bullet\,$  encoder measurements 2 data @ 10 Hz
- Sampling frequency: 10 Hz

## ERC HIGHWIND project

#### Timing results: MHE & NMPC

		Average	Worst case
MHE	Preparation phase Estimation phase	3.76 ms 0.75 ms	3.76 ms 0.78 ms
	Overall execution time	4.51 ms	4.54 ms
MPC	Preparation phase Feedback phase	3.56 ms 0.50 ms	3.56 ms 0.61 ms
	Overall execution time	4.06 ms	4.17 ms

## MHE applied on an induction motor [Frick, 2012]<sup>2</sup>

Dynamic system properties:

- 5 states, 2 controls
- 6 estimation intervals
- sampling freq.: 1.5 kHz



Execution times:

- one RTI on a 3 GHz Intel CPU: 30 μs (double precision)
- one RTI on a 1 GHz TI low power DSP: 270 μs (single precision)

<sup>&</sup>lt;sup>2</sup>Joint work with ETH Zürich (D. Frick, A. Domahidi, S. Mariethoz, M. Morari)

# Overhead crane [Debrouwere, 2014]



linear input $ ightarrow$ no	onlinear $ ightarrow$	linear output
6	2	0
	unstructured	d structured
integration method	<b>220</b> μ	s 67 μs
condensing	6 µ	s бµs
QP solution (qpOASES	) 16 µ	s 16 µs
remaining operations	3 µ	s 3µs
one real-time iteration	245 µ	s 92 µs

Table : T = 1.0 s, N = 10 and 4<sup>th</sup> order Gauss method (h = 0.025 s)

<sup>&</sup>lt;sup>3</sup>Intel i7-3720QM 6MB cache, 2.60 GHz

linear input $ o$ nor	linear $ ightarrow$ linear	near output
6	2	0
	unstructured	structured
integration method	220 μs	<b>67</b> μs
condensing	6 µs	б µs
QP solution (qpOASES)	16 µs	16 µs
remaining operations	3 µs	3 µs
one real-time iteration	245 µs	92 µs

Table : T = 1.0 s, N = 10 and 4<sup>th</sup> order Gauss method (h = 0.025 s)

 $\Rightarrow$  integration speedup factor  $\sim 3$ 

<sup>&</sup>lt;sup>3</sup>Intel i7-3720QM 6MB cache, 2.60 GHz

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#### Let's control the Van der Pol oscillator





Van der Pol oscillator x,x' phase diagram for epsilon= $\alpha = 1$ 

$$dot(x_1) = (1 - x_2^2)x_1 - x_2 + u$$
$$dot(x_2) = x_1$$

#### Thank you for your attention!

**Questions?**