The acados software package

an open-source framework for fast embedded optimal control

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universität freiburg

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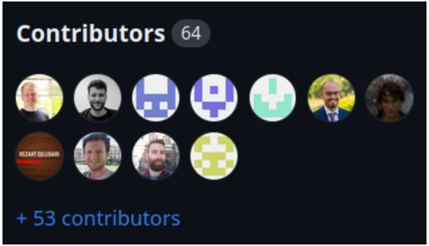

github.com/acados/acados

R. Verschueren, G. Frison, D. Kouzoupis, J. Frey, N. van Duijkeren, A. Zanelli, B. Novoselnik, T. Albin, R. Quirynen, M. Diehl (2021): *acados – a modular open-source framework for fast embedded optimal control*, Mathematical Programming Computation

Building blocks

acados provides several building blocks for nonlinear optimal control

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- Integrators for ODEs and DAEs
  - explicit and (structure-exploiting) implicit Runge-Kutta schemes
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  - `HPIPM`, `qpOASES`, `qpDUNES`, `OSQP`, `DAQP`

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- Interfaces to state-of-the-art QP solvers
  - HPIPM, qpOASES, qpDUNES, OSQP, DAQP
- Generation of self-contained C code for embedded deployment as well as convenient user interfaces to MATLAB and python.

Dependencies

acados builds on

- CasADi[1] for describing the problem functions and their derivatives via algorithmic differentiation (AD)

[1]Andersson et al., 2019; [2]Frison & Diehl, 2020; [3]Frison et al., 2018; [4]Ferreau et al., 2014; [5]Frasch et al., 2015; [6]Stellato et al., 2020; [7]Arnstrom et al., 2022;

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- various open-source QP solvers, HPIPM[2], qpOASES[4], qpDUNES[5], OSQP[6], DAQP[7], for solving the SQP-subproblems

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Learning for MPC. MPC for Learning.

- Neural networks and Gaussian processes as part of the NMPC formulation, e.g. Salzmann et al., 2023; Lahr et al., 2023; Gordon et al., 2022.

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- Custom sensitivity propagation for accurate cost integration for convex-over-nonlinear costs (Frey, Baumgärtner, & Diehl, 2023)
- Convenient and efficient access to the SQP subproblem for custom modifications (Frey, Gao, et al., 2023)

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- Electric Motor Control (Zanelli et al., 2021)
- Autonomous Racing Control (Tearle et al., 2021)

Call for participation

We highly appreciate contributions and collaborations (related) to acados.

- Interfaces to QP solvers
- Benchmarks
  - control problem formulation, problem discretization, problem approximations within the NMPC context
  - embedded performance
- (Embedded) deployment of acados in real-world applications
- ...

Summary

- acados is an open-source software package providing several building blocks for nonlinear optimal control
- acados supports generation for self-contained C code for embedded deployment
- acados has been applied successfully in various experimental settings

- We highly appreciate contributions and collaborations on acados related project.

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Continuous-time optimal control problem

Continuous-time optimal control problem (OCP):

$$
\begin{aligned}
\underset{x(\cdot),z(\cdot),u(\cdot)}{\text{minimize}} \quad & \int_{t=0}^{T} \ell(x(t), z(t), u(t)) \, \mathrm{d}t + M(x(T)) \\
\text{subject to} \quad & x(0) = \bar{x}_0, \\
& 0 = f(\dot{x}(t), x(t), z(t), u(t)), \quad t \in [0, T], \\
& 0 \geq g(x(t), z(t), u(t)), \qquad\quad t \in [0, T].
\end{aligned} \tag{1}
$$

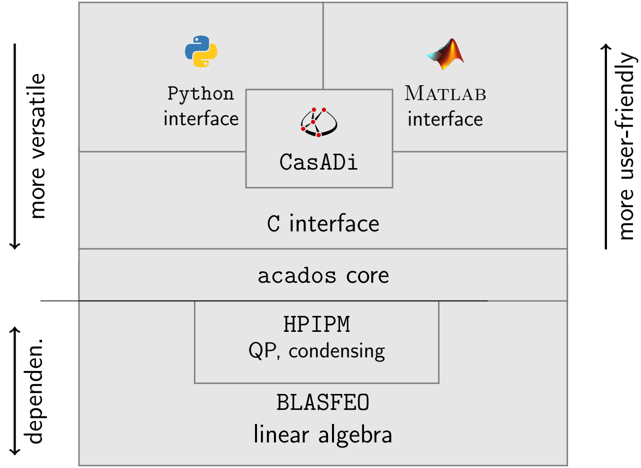
In MPC, instances of these problems are solved repeatedly, with current state $\bar{x}_0$.

OCP structured NLP handled in acados

$$
\begin{aligned}
\underset{\substack{x_0,\ldots,x_N,\\ u_0,\ldots,u_{N-1},\\ z_0,\ldots,z_{N-1},\\ s_0,\ldots,s_N}}{\text{minimize}} \quad & \sum_{k=0}^{N-1} l_k(x_k,u_k,z_k) + M(x_N) + \sum_{k=0}^{N} \rho_k(s_k) && && \text{(2a)}\\
\text{subject to} \quad & \begin{bmatrix} x_{k+1} \\ z_k \end{bmatrix} = \phi_k(x_k,u_k), && k = 0,\ldots,N-1, && \text{(2b)}\\
& 0 \geq g_k(x_k,z_k,u_k) - J_{\mathrm{s},k} s_k && k = 0,\ldots,N-1, && \text{(2c)}\\
& 0 \geq g_N(x_N) - J_{\mathrm{s},N} s_N, && && \text{(2d)}\\
& 0 \leq s_k && k = 0,\ldots,N. && \text{(2e)}
\end{aligned}
$$

- ϕ_k – discrete time dynamics on $[t_k, t_{k+1}]$ – typically acados integrator from ODE or DAE
- l_k – approximation of Lagrange cost term ℓ on $[t_k, t_{k+1}]$
- efficient support for slack variables s_k
- inequality constraints g_k
- problem functions can vary stage wise

Structure of the acados software



The interplay between the acados dependencies, the 'core' C library and its interfaces.

- BLASFEO: Basic Linear Algebra for Embedded Optimization
- HPIPM: High-Performance Interior Point Method

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