ParaOpt algorithm for unstable system

Norbert Tognon & Julien Salomon

INRIA Paris

DD27 Prague, July 2022.

Table of contents

ParaOpt Algorithm

2 ParaOpt for Dahlquist problems

3 Numerical results

Optimal control problem

Let us consider the **optimal control problem** on a fixed, bounded interval [0, T].

Cost functional

$$J(\nu) = \frac{1}{2} ||y(T) - y_{target}||^2 + \frac{\alpha}{2} \int_0^T \nu^2(t) dt,$$

- α : a fixed regularization parameter;
- y_{target}: the target state;
- ν : the control;
- y: state function is described by the equation

$$\begin{cases} \dot{y}(t) = f(y(t)) + \nu(t), & t \in [0; T] \\ y(0) = y_{init}. \end{cases}$$
 (1)

Optimality System

Linear control case

	Linear eq.	Non-linear eq.
"Linear" control	$\dot{y} = Ay + B\nu$	$\dot{y} = f(y) + B\nu$
Non-linear control	$\dot{y} = A(\nu)y$	$\dot{y} = f(y, \nu)$

Lagrange operator

$$\mathcal{L}(y,\lambda,\nu) = J(\nu) - \int_0^T \langle \lambda(t),\dot{y}(t) - f(y(t)) - \nu(t) \rangle dt.$$

Optimality System

Optimality system

$$\begin{cases} \dot{y}(t) = f(y(t)) + \nu(t), \\ \dot{\lambda}(t) = -(f(y)')^{T} \lambda(t), \quad \text{and} \quad \begin{cases} y(0) = y_{init} \\ \lambda(T) = y(T) - y_{target}. \end{cases}$$

 \longrightarrow Elimination of ν

$$\begin{cases} \dot{y} = f(y) - \frac{\lambda}{\alpha}, \\ \dot{\lambda} = -(f(y)')^T \lambda, \end{cases}$$
 (2)

with initial and final condition respectively $y(0) = y_{init}$ and $\lambda(T) = y(T) - y_{target}$.

Optimality system on subintervals

• $[0, T] = \bigcup_{\ell=0}^{L-1} [T_{\ell}, T_{\ell+1}], \quad T_{\ell} = \ell \Delta T.$

$$(S_0) \qquad (S_1) \qquad (S_{l-1})$$

$$\downarrow \qquad \qquad \downarrow \qquad \qquad \uparrow \qquad \qquad \downarrow \qquad \qquad$$

Subproblem notation

$$\begin{cases} \dot{y}_{\ell} = f(y_{\ell}) - \frac{\lambda_{\ell}}{\alpha}, \\ \dot{\lambda} = -f'(y_{\ell})^{T} . \lambda_{\ell}, \end{cases} \quad \text{and} \quad \begin{cases} y(T_{\ell}) = Y_{\ell} \\ \lambda(T_{\ell+1}) = \Lambda_{\ell+1}, \end{cases}$$

where Y_{ℓ} and Λ_{ℓ} are the approximations of y and λ in $T_{\ell}, \ell = 1, \dots, L$ respectively.

Optimality system with matching conditions

Denoting

$$\begin{bmatrix} y(T_{\ell+1}) \\ \lambda(T_{\ell}) \end{bmatrix} = \begin{bmatrix} P(Y_{\ell}, \Lambda_{\ell+1}) \\ Q(Y_{\ell}, \Lambda_{\ell+1}) \end{bmatrix}.$$

• The optimality system is enriched:

$$\begin{array}{rclcrcl} Y_0 - y_{init} & = & 0 \\ Y_1 - P(Y_0, \Lambda_1) & = & 0 & \Lambda_1 - Q(Y_1, \Lambda_2) & = & 0 \\ Y_2 - P(Y_1, \Lambda_2) & = & 0 & \Lambda_2 - Q(Y_2, \Lambda_3) & = & 0 \\ & \vdots & & & \vdots & & \vdots \\ Y_L - P(Y_{L-1}, \Lambda_L) & = & 0 & \Lambda_L - Y_L + y_{target} & = & 0 \end{array}$$

We have that a system of boundary value subproblems, satisfying matching conditions.

Optimality system in compact form

Collecting the unknowns in the vector

$$(Y^{T}, \Lambda^{T}) := (Y_{0}, Y_{1}, Y_{2}, \dots, Y_{L}, \Lambda_{1}, \Lambda_{2}, \dots, \Lambda_{L}),$$

we obtain the nonlinear system

$$\mathcal{F}\begin{pmatrix} Y_{0} - y_{init} \\ Y_{1} - P(Y_{0}, \Lambda_{1}) \\ Y_{2} - P(Y_{1}, \Lambda_{2}) \\ \vdots \\ Y_{L} - P(Y_{L-1}, \Lambda_{L}) \\ \Lambda_{1} - Q(Y_{1}, \Lambda_{2}) \\ \Lambda_{2} - Q(Y_{2}, \Lambda_{3}) \\ \vdots \\ \Lambda_{L} - Y_{L} + y_{target} \end{pmatrix} = 0.$$
(3)

Newton method

Newton method

$$\mathcal{F}'\begin{pmatrix} Y^k \\ \Lambda^k \end{pmatrix}\begin{pmatrix} Y^{k+1} - Y^k \\ \Lambda^{k+1} - \Lambda^k \end{pmatrix} = -\mathcal{F}\begin{pmatrix} Y^k \\ \Lambda^k \end{pmatrix},$$

where

$$\mathcal{F}'\binom{Y}{\Lambda} := \begin{pmatrix} I & & & & & & \\ -P_y(Y_0, \Lambda_1) & I & & & & & \\ & \ddots & \ddots & & & & \ddots & & \\ & & -P_y(Y_{L-1}, \Lambda_L) & I & & & & -P_{\lambda}(Y_0, \Lambda_1) \\ & & & -P_{\lambda}(Y_0, \Lambda_1) & & & & & \\ & & & \ddots & & & & \\ & & -Q_y(Y_1, \Lambda_2) & & & I & -Q_{\lambda}(Y_1, \Lambda_2) \\ & & & \ddots & & & & \\ & & -Q_y(Y_{L-1}, \Lambda_L) & & & & I & -Q_{\lambda}(Y_{L-1}, \Lambda_L) \\ & & & -I & & & I \end{pmatrix}$$

Coarse approximation of Jocabian matrix

• \mathcal{J}^G coarse approximation of Jacobian matrix \mathcal{F}' using **derivative Parareal** idea, which corresponds to:

$$\begin{split} P_{y}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(Y_{\ell-1}^{k+1}-Y_{\ell-1}^{k}) &\approx \ P_{y}^{G}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(Y_{\ell-1}^{k+1}-Y_{\ell-1}^{k}), \\ P_{\lambda}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(\Lambda_{\ell}^{k+1}-\Lambda_{\ell}^{k}) &\approx \ P_{\lambda}^{G}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(\Lambda_{\ell}^{k+1}-\Lambda_{\ell}^{k}), \\ Q_{\lambda}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(\Lambda_{\ell}^{k+1}-\Lambda_{\ell}^{k}) &\approx \ Q_{\lambda}^{G}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(\Lambda_{\ell}^{k+1}-\Lambda_{\ell}^{k}), \\ Q_{y}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(Y_{\ell-1}^{k+1}-Y_{\ell-1}^{k}) &\approx \ Q_{y}^{G}(Y_{\ell-1}^{k},\Lambda_{\ell}^{k})(Y_{\ell-1}^{k+1}-Y_{\ell}^{k}). \end{split}$$

- The computation of $P_y^G, P_\lambda^G, Q_y^G$ and Q_λ^G involves linear problems on the subintervals in parallel using coarse solver.
- → **Derivative Parareal**: M. Gander and E. Hairer, Analysis for parareal algorithms applied to Hamiltonian differential equations, 2014.

Inexact Newton method

Inexact Newton method

$$\mathcal{J}^{G}\begin{pmatrix} Y^{k} \\ \Lambda^{k} \end{pmatrix} \begin{pmatrix} Y^{k+1} - Y^{k} \\ \Lambda^{k+1} - \Lambda^{k} \end{pmatrix} = -\mathcal{F}\begin{pmatrix} Y^{k} \\ \Lambda^{k} \end{pmatrix}.$$

→ **ParaOpt**: M. Gander, K. Felix, J. Salomon, ParaOpt: A Parareal algorithm for optimal control systems.

• Let us consider the **Dahlquist problem**

$$\dot{y}(t) = \sigma y(t) + \nu(t),$$

where σ is real number.

Linear equation case

	Linear eq.	Non-linear eq.
"Linear" control	$\dot{y} = Ay + B\nu$	$\dot{y} = f(y) + B\nu$
Non-linear control	$\dot{y} = A(\nu)y$	$\dot{y} = f(y, \nu)$

• Let $\Delta t = \Delta T/M$ and $\delta t = \Delta T/N$ such that $\delta t \leq \Delta t \leq \Delta T$.

Definition of solutions operators

• Negative σ case: backward Euler method

$$P(Y_{\ell}, \Lambda_{\ell+1}) := \beta_{\delta t} Y_{\ell} - \frac{\gamma_{\delta t}}{\alpha} \Lambda_{\ell+1},$$
$$Q(Y_{\ell}, \Lambda_{\ell+1}) := \beta_{\delta t} \Lambda_{\ell+1},$$

with

$$eta_{\delta t} := (1 - \sigma \delta t)^{-\frac{\Delta I}{\delta t}},$$

$$\gamma_{\delta t} := \frac{\beta_{\delta t}^2 - 1}{\sigma (2 + \sigma \delta t)}.$$

• Positive $\sigma > 0$ case: forward Euler method

$$P(Y_{\ell}, \Lambda_{\ell+1}) := \beta_{\delta t} Y_{\ell} - \frac{\gamma_{\delta t}}{\alpha} \Lambda_{\ell+1},$$
$$Q(Y_{\ell}, \Lambda_{\ell+1}) := \beta_{\delta t} \Lambda_{\ell+1},$$

with

$$\beta_{\delta t} := (1 + \sigma \delta t)^{\frac{\Delta T}{\delta t}},$$

$$\gamma_{\delta t} := \frac{\beta_{\delta t}^2 - 1}{\sigma(2 + \sigma \delta t)}.$$

Linear form of ParaOpt

ParaOpt algorithm becomes

$$\begin{aligned} M_{\Delta t}(X^{k+1} - X^k) &= -(M_{\delta t}X^k - b), \\ X &= (Y, \Lambda)^T, \quad b = (y_{init}, 0, \dots, 0, -y_{target})^T, \end{aligned}$$

Negative σ case

Theorem (M. Gander et al.)

Let ΔT , Δt , δt and α be fixed. Then for all $\sigma < 0$, the spectral radius of $\left(\text{Id} - M_{\Delta t}^{-1} M_{\delta t} \right)$ satisfies

$$\max
ho(\sigma)_{\sigma < 0} < rac{0.79 \Delta t}{lpha + \sqrt{lpha \Delta t}} + 0.3.$$

Thus, if $\alpha > 0.4544\Delta t$, then the linear Paraopt algorithm converges.

Analysis of positive σ case

- Let μ be a nonzero eigenvalue of $(Id M_{\Delta t}^{-1} M_{\delta t})$.
- $\beta = \beta_{\Delta t}$, $\gamma = \gamma_{\Delta t}$, $\delta \beta = \beta \beta_{\delta t}$, $\delta \gamma = \gamma \gamma_{\delta t}$.
- $\tau = \beta \gamma \delta \beta / \delta \gamma$.
- We have $1 < \tau < \beta$, $\delta \beta < 0$ and $\delta \gamma < 0$.
- ullet Let ψ be a function defined on $]1,\infty[$ by

$$\psi(x) = x^{2L-2}(x-1) - x + \frac{1}{\beta}.$$

Analysis of positive σ case

- ψ has only one root τ_0 in $]1,\infty[$.
- Let L_0 be

$$L_0 = \frac{(\beta - \tau)}{\gamma(\tau - \tau_0)}.$$

Theorem

Let $\sigma > 0, \alpha, T, L, \Delta t, \delta t$ and be fixed. If $\psi(\tau) > 0$ and L satisfies $L > \alpha L_0$ then, the spectral radius of $\left(\text{Id} - M_{\Delta t}^{-1} M_{\delta t} \right)$ satisfies

$$\rho < (\Delta t - \delta t) C(\sigma, \Delta T),$$

where

$$\mathcal{C}(\sigma, \Delta T) = \left[rac{1}{2}\sigma + \sigma\left(rac{1}{2}\sigma(\Delta t - \delta t) + 1
ight)e^{2\sigma\Delta T}
ight].$$

Analysis of positive σ case

ullet The eigenvalues μ are roots of the polynomial

$$f(\mu) := \alpha \frac{\delta \beta}{\delta \gamma} + \left(\gamma \frac{\delta \beta}{\delta \gamma} + \mu^{-1} \delta \beta \right) \sum_{\ell=0}^{L-1} \left(\beta - \mu^{-1} \delta \beta \right)^{2\ell}.$$

• Change of variable $\mu = \frac{\delta \beta}{\beta - \mathbf{z}}$

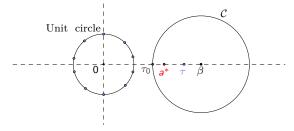
$$f_1(z) := \alpha \frac{\delta \beta}{\delta \gamma} - (\tau - z) \sum_{\ell=0}^{L-1} z^{2\ell}.$$

• $\mathcal{C} := \{z \in \mathbb{C}, |z - \beta| < (\beta - \tau_0)\}$ and

$$h(z) := (\tau - z) \sum_{\ell=0}^{L-1} z^{2\ell}.$$

Analysis of positive σ case

- $\psi(\tau) > 0$ and $L > \alpha L_0$, $|f_1(z) h(z)| < |h(z)|$ on C.
- Using Rouché's theorem, f_1 has only one root a^* inside C.



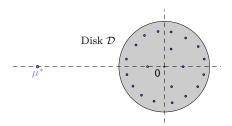
- a* is real number.
- $\tau_0 < a^* < \tau$, so that

$$f_1(z) = \alpha \frac{\delta \beta}{\delta \gamma} - (\tau - z) \sum_{l=0}^{L-1} z^{2l} > 0, \quad \text{for } z \in]\tau, \infty[.$$

Analysis of positive σ case

ullet Eigenvalues associated with the roots of f_1 outside ${\mathcal C}$ lie in the disk

$$\mathcal{D} := \{ z \in \mathbb{C} : |z| \leq \frac{|\delta \beta|}{(\beta - \tau_0)} \}.$$



• The eigenvalue associated with a^* is $\mu^* = \delta \beta / (\beta - a^*) < 0$.

Analysis of positive σ case

ullet The spectral radius is determined by μ^* then

$$\rho = |\mu^*| < \frac{|\delta\beta|}{\beta - \tau} = \frac{|\delta\gamma|}{\gamma}.$$

In first time

$$\frac{|\delta\gamma|}{\gamma} \leq \frac{\sigma}{2}(\Delta t - \delta t) + \left[\frac{\sigma}{2}(\Delta t - \delta t) + 1\right] \frac{\beta_{\delta t}^2 - \beta^2}{\beta^2 - 1}.$$

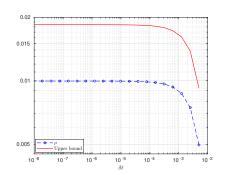
And

$$\frac{\beta_{\delta t}^2 - \beta^2}{\beta^2 - 1} \le \sigma(\Delta t - \delta t)e^{2\sigma\Delta t}.$$

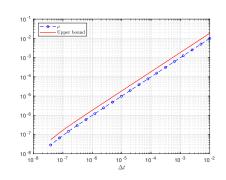
Numerical example

We fix
$$T = 1$$
, $\sigma = 1$, $\alpha = 0.1$ and $L = 10$.

$$\Delta t = 10^{-2}.T, \delta t = \Delta t/2^k, k = 0, \dots, 20.$$

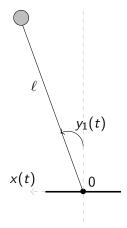


$$\delta t = 5.2^{-20}.10^{-2}, \Delta t = 10^{-2}.2^{-k}, k = 1, 2, \dots, 18.$$



Numerical example: Inverted pendulum

Inverted pendulum



Equation of the system

$$\ddot{y}_1(t) = \omega^2 \sin y_1(t) - \ddot{x}(t) \cos y_1(t),$$
with $\omega = \sqrt{\frac{g}{\ell}}.$

Numerical example: Inverted pendulum

• Let $y = (y_1, y_2)$,

$$\dot{y}_1(t) = y_2(t)$$

 $\dot{y}_2(t) = \omega^2 \sin y_1(t) + \nu(t) \cos y_1(t),$

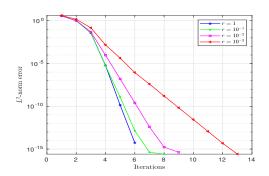
where $\nu = -\ddot{x}$.

Non-linear control case :

	Linear eq.	Non-linear eq.
"Linear" control	$\dot{y} = Ay + B\nu$	$\dot{y} = f(y) + B\nu$
Non-linear control	$\dot{y} = A(\nu)y$	$\dot{y}=f(y,\nu)$

Numerical example: Inverted pendulum

- $T = 1, \alpha = 10^{-2}, L = 8, g = 9.81, \ell = 0.5, \delta t = 2.10^{-5} T.$
- $y_{init} = (\frac{\pi}{4}, \frac{\pi}{6}), y_{target} = (0, 0), r = \frac{\delta t}{\Delta t}$.



Bibliography



M. Gander, F. Kwok and J. Salomon

ParaOpt: A parareal algorithm for optimal control systems.

SIAM Journal on Scientific Computing, 42(5): A2773-A2802, 2020.



H. Kalmus.

The inverted pendulum.

American journal of Physics, 38(7):874–778, 1970...

Thank you for your attention!