## Optimized Schwarz Method in Time Direction for Transport Control

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This work is financially supported by the ANR project ALLOWAP under grant ANR-19-CE46-0013

Seminar IDEFIX team, ENSTA Paris, 20 March 2023









## Motivation

We are interested in optimization problems governed by hyperbolic partial differential equations (PDEs) from inverse problem/data assimilation.



Figure: Expérience de sismique réflexion.

- Model :  $\dot{x}_{ref}(t) = Ax_{ref}(t) + Bv(t)$ .
- Linear data :  $y_{ref}(t) = Cx_{ref}(t)$ .

Objective function :  

$$J(u) = \frac{1}{2}F_1(\|Cx_{\text{ref}} - y_{\text{obs}}\|) + F_2(\|v\|)$$

### Difficulties

- large amounts of data to process
- high resolution required.
- backward-Forward optimization loops.

 $\Rightarrow$  essential to design scalable, highly efficient parallelel methods.

## **Domain Decomposition Methods**

Replace solving a PDE in a large/complex domain by solving successively the same PDE in the smaller/simpler subdmains

### For PDEs

- Overlapping Schwarz Method
  - · · · [Schwarz 1870]
- Non-overlapping + Robin conditions
   ... Lions (1990).
- Optimized conditions
   ... [Japhet-Nataf 2001], [Gander 2006].

### For Optimal Control Problem

 Schwarz Method for eliptic optimal control

··· [Benamou 1994], [Benamou-Desprès 1996]

#### For time-dependent PDEs

- Parareal
  - ···· [Lions-Maday-Turinici 01], [Gander-Vandewalle 07]

#### Space-Time DD

···· [Gander-Halpern-Nataf 99], [Gander-Kwok-Mandal 16]

### For Time Optimal Control Problem

- PinT in optimization loops
   ···[Götschel-Minion 19], [Günther and al. 19]
- ParaOpt · · · [Gander-Kwok-Salomon 20]
- Domain decomposition in Time direction.
   ... [Gander-Kwok 16], [Leugering and al. 21]

### Discription of the problem

Let T > 0, and  $y_{ini}, y_{tar} \in L^2(\mathbb{R})$ . We find a control  $v \in L^2(0, T, L^2(\mathbb{R}))$  s.t. y defined by

$$\begin{cases} \partial_t y + \partial_x y = v & \text{ in } \mathbb{R} \times (0, T), \\ y(., 0) = y_{\text{ini}}, \end{cases}$$

verifies the exact constraint

$$y(., T) = y_{tar}.$$

We shall seek v that minimize the functional

$$J(v) = \frac{1}{2} \int_0^T \|v\|_{L^2(\mathbb{R})}^2.$$

The above optimization problem has a unique solution  $v^* \in L^2(\mathbb{R} \times (0, T))$ , given by

$$v^* = \lambda,$$

where,

$$\begin{cases} \partial_t y + \partial_x y = \lambda \\ \partial_t \lambda + \partial_x \lambda = 0 \end{cases} \quad y(t=0) = y_{\text{ini}}, y(t=T) = y_{\text{tar}} \tag{1}$$

Equivalent PDEs in y

$$\partial_{tt}y + 2\partial_{tx}y + \partial_{xx}y = 0$$

with 2-point boundary at t = 0 and  $t = T \Rightarrow$  Schwarz Method.

## OUTLINE



### Schwarz Method for continuous settings

- Schwarz Method for discrete model
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## Time Direction Schwarz Algorithm

Starting with  $(y_1^0, \lambda_1^0)$  and  $(y_2^0, \lambda_2^0)$ , at iteration  $k \ge 1$ , we solve

$$\begin{cases} \partial_t y_1^k + \partial_x y_1^k &= \lambda_1^k \\ \partial_t \lambda_1^k + \partial_x \lambda_1^k &= \mathbf{0} \end{cases} \qquad \begin{cases} \partial_t y_2^k + \partial_x y_2^k &= \lambda_2^k \\ \partial_t \lambda_2^k + \partial_x \lambda_2^k &= \mathbf{0} \end{cases}$$



Subdomain system is equivalent with an optimal control problem  $\cdots$  [Leugeuring and al. 2021]

### Convergence

#### Theorem

The optimal choice is  $p = \frac{1}{\Delta T}$ ,  $q = \frac{1}{\Delta T}$ , which leads to an immediate convergence after 2 iterations.

#### Remark

For general *N* time windows, with  $p_i = \frac{1}{2^{i-1}\Delta T}$  and  $q_i = \frac{1}{2^{N-i-1}\Delta T}$ , the method converges after *N* iterations.



## Proof: Fourrier analysis

Using Fourier transform in space :

For  $\hat{y}_{ini}, \hat{y}_{tar} \in \mathbb{C}$ , we minimize

$$\min_{\hat{\boldsymbol{\nu}}\in L^2(0,T)}J(\hat{\boldsymbol{\nu}})=\frac{1}{2}\int_0^T|\hat{\boldsymbol{\nu}}|^2$$

where the control  $\hat{v}$  is such that  $\hat{y}$ 

$$\begin{cases} \partial_t \hat{y} + i\omega \hat{y} = \hat{v} & t \in (0, T), \\ \hat{y}(0) = \hat{y}_{ini}, \end{cases}$$

satisfies

$$\hat{y}(T) = \hat{y}_{tar}$$

The unique solution  $\hat{v}^* \in L^2(0, T)$  is given by

$$\hat{\mathbf{v}}^* = \hat{\lambda},$$

where,

$$\begin{cases} \partial_t \hat{y} + i\omega \hat{y} = \hat{\lambda} \\ \partial_t \hat{\lambda} + i\omega \hat{\lambda} = \mathbf{0} \end{cases} \qquad \hat{y}(\mathbf{0}) = \hat{y}_{\text{ini}}, \hat{y}(T) = \hat{y}_{\text{tar}} \end{cases}$$
(2)

## Fourier Analysis setting: Convergence Factor

Let  $\hat{y}_{ini} = \hat{y}_{tar} = 0$ . Denote by  $\hat{\xi}_i^k$  the Robin terms.

Starting from  $\hat{\xi}_1^0$  and  $\hat{\xi}_2^0$ , at iteration  $k \ge 1$ , we solve (2) in  $(0, \Delta T)$  and  $(\Delta T, T)$  with

$$\begin{array}{rcl} q\hat{y}_{1}^{k} + \hat{\lambda}_{1}^{k} &= \xi_{1}^{k-1} \\ -p\hat{y}_{2}^{k} + \hat{\lambda}_{2}^{k} &= \xi_{2}^{k-1} \end{array} \quad \text{then update} \quad \begin{array}{rcl} \hat{\xi}_{1}^{k} &= q\hat{y}_{2}^{k} + \hat{\lambda}_{2}^{k} \\ \hat{\xi}_{2}^{k} &= -p\hat{y}_{1}^{k} + \hat{\lambda}_{1}^{k} \end{array}$$

Convergence factor is the  $\sqrt{|\rho|}$  defined by

$$\hat{\xi}_i^k = \rho \hat{\xi}_i^{k-2}$$

$$\rho := \rho(\boldsymbol{p}, \boldsymbol{q}) = \frac{1 - \boldsymbol{p} \Delta T}{1 + \boldsymbol{p} \Delta T} \cdot \frac{1 - \boldsymbol{q} \Delta T}{1 + \boldsymbol{q} \Delta T}$$

## OUTLINE

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### Fully discrete optimal control problem

We consider y and v periodic in space of periodic one.

$$\min_{v^1,\ldots,v^M\in\mathbb{R}^{N_x}}J(v^1,\ldots,v^M)=\Delta x\Delta t\frac{1}{2}\sum_{m=1}^M\|v^m\|_{\mathbb{R}^{N_x}}^2$$

where the control  $(v^1, \ldots, v^M)$  is s.t.  $(y_0, \ldots, y_M)$  verifies, for  $m = 1, \ldots, M$ 

$$\begin{cases} \frac{y_j^m - y_j^{m-1}}{\Delta t} + \frac{y_j^{m-1} - y_{j-1}^{m-1}}{\Delta x} = v_j^m, \\ y_j^0 = y_{\text{ini},j}, \end{cases}$$

satisfies  $y_j^M = y_{\text{tar},j}$ .

### Remark

At 
$$t_1 = \Delta t$$
, for  $y_{\text{ini}} = 0$ ,  $y(., \Delta t) = \Delta t v(., \Delta t) \Rightarrow v_j^{m-1} \rightarrow v_j^m$ .

$$\begin{cases} \frac{y_j^m - y_j^{m-1}}{\Delta t} + \frac{y_j^{m-1} - y_{j-1}^{m-1}}{\Delta x} = \lambda_j^m, \\ \frac{\lambda_j^{m-1} - \lambda_j^m}{\Delta t} + \frac{\lambda_j^m - \lambda_{j+1}^m}{\Delta x} = 0, \\ y_j^0 = y_{\text{ini},j}, y_j^M = y_{\text{tar},j} \end{cases}$$

### Convergence

$$T = 1, \Omega = (0, 1), \Delta t = 1/160, r = 1/2;$$



 $\Rightarrow$  We do not have convergence after 2 iterations!

## **Discrete Fourier Analysis**

**Discrete Fourier Transform** 

$$\frac{y_j^{m-1}-y_{j-1}^{m-1}}{\Delta x} \to \sigma(\ell)\hat{y}^m, \quad \frac{\lambda_j^m-\lambda_{j+1}^m}{\Delta x} \to \bar{\sigma}(\ell)\hat{\lambda}^n$$

with 
$$\sigma(\ell) = \frac{1 - e^{-2\pi i \ell \Delta x}}{\Delta x}, \ \ell = 0, \dots, N_x - 1.$$

$$\frac{\hat{y}^{m} - \hat{y}^{m-1}}{\hat{\Delta}t} + \sigma(\ell)\hat{y}^{m-1} = \hat{\lambda}^{m} \\
\frac{\hat{\lambda}^{m} - \hat{\lambda}^{m-1}}{\Delta t} - \bar{\sigma}\hat{\lambda}^{m} = 0 \\
y^{0} = \hat{y}_{\text{ini}} \\
y^{M} = \hat{y}_{\text{tar}}$$
(3)

 $rac{\Delta t}{\Delta x} = r ext{ fixed} 
ightarrow ext{maximum of } \ell ext{ is of order } (\Delta t)^{-1}.$ 

### Convergence factor



We solve (3) in  $(0, \Delta T)$  (m = 1, ..., M/2) and in  $(\Delta T, T)$  (m = M/2 + 1, ..., M) with the transmission conditions at the interface m = M/2

$$q\hat{y}_1^{k,M/2} + \hat{\lambda}_1^{k,M/2} = \hat{\xi}_1^{k-1} \qquad -p\hat{y}_2^{k,M/2} + \hat{\lambda}_2^{k,M/2} = \hat{\xi}_2^{k-1}$$

Then update

$$\hat{\xi}_1^k = q \hat{y}_2^{k,M/2} + \hat{\lambda}_2^{k,M/2} \qquad \hat{\xi}_2^k = -p \hat{y}_1^{k,M/2} + \hat{\lambda}_1^{k,M/2}$$

We get  $\hat{\xi}^k_i = \rho \hat{\xi}^{k-2}_i$  with

$$\rho := \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{q}, \ell) = \frac{1 - \boldsymbol{p} \gamma_{\Delta t}(\ell)}{1 + \boldsymbol{q} \gamma_{\Delta t}(\ell)} \cdot \frac{|\beta_{\Delta t}(\ell)|^2 - \boldsymbol{q} \gamma_{\Delta t}(\ell)}{|\beta_{\Delta t}(\ell)|^2 + \boldsymbol{p} \gamma_{\Delta t}(\ell)}$$

where  $\beta_{\Delta t}(\ell) = (1 - \sigma(\ell)\Delta t)^{M/2}$ , and  $\gamma_{\Delta t}(\ell) = \Delta t \sum_{m=0}^{M/2-1} |1 - \sigma(\ell)\Delta t|^{2m}$ .

## Minimax Propblem

The convergence factor depends on  $\ell$  and on  $\Delta t$  ( $\Delta x$  fixed by  $\Delta t$ ), denoted by  $\rho_{\Delta t}$ 

$$\min_{p,q>0} \max_{\ell=0,\ldots,N_x-1} |\rho_{\Delta t}(p,q,\ell)| \tag{4}$$

 $\rho_{\Delta t}$  is a function in

$$|1 - \Delta t \sigma(\ell)|^2 = 1 - 4r(1 - r)\sin^2\left(\pi \ell \Delta x\right)$$

⇒ new variable  $s = 4r(1 - r) \sin^2(\pi \omega \Delta x)$ ,  $s \in [0, s_{max}]$  with  $s_{max} = 4r(1 - r)$ . Optimial parameters  $\frac{1}{\Delta T} \Rightarrow p\Delta T$  and  $q\Delta T$  as parameters. New minimax problem

$$\min_{p,q>0} \max_{0 \le s \le s_{\max}} |\rho_{\Delta t}(p,q,s)| \tag{5}$$

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### One parameter case p = q

 $\rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{s}) := \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{p}, \boldsymbol{s})$ 

$$\min_{\boldsymbol{\rho} > 0} \max_{0 \le s \le s_{\max}} |\rho_{\Delta t}(\boldsymbol{\rho}, \boldsymbol{s})| \tag{6}$$

#### Theorem

For  $\Delta t$  small enough, Problem (6) has a unique solution  $p_{\Delta t}^*$ . As  $\Delta t$  goes to 0,

$$\begin{split} p^*_{\Delta t} &= \sqrt{2\Delta T} \; s_{\max}.\Delta t^{-1/2} + o\left(\Delta t^{-1/2}\right),\\ \max_{0 \leq s \leq s_{\max}} \left| \rho_{\Delta t}(s, \boldsymbol{p}^*_{\Delta t}) \right| &= 1 - \frac{2\sqrt{2}}{\sqrt{\Delta T} \; s_{\max}} \cdot \Delta t^{1/2} + o\left(\Delta t^{1/2}\right). \end{split}$$

### Sketch of the proof

Step 1 : Solution of alternation equation

Let 
$$p_{\max} = \frac{\Delta T}{\gamma_{\Delta t}(s_{\max})}.$$

$$\max_{0 \le s \le s_{\max}} \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{z}) = -\min_{0 \le z \le s_{\max}} \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{s}).$$

has a unique solution  $1 < p^*_{\Delta t} < p_{max}$ . We introduce

$$\rho_{\Delta t,\max}(\boldsymbol{p}) = \max_{0 \le s \le s_{\max}} \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{z}), \quad \rho_{\Delta t,\min}(\boldsymbol{p}) = \min_{0 \le s \le s_{\max}} \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{z}),$$

and the function

$$f = \rho_{\Delta t, \max} + \rho_{\Delta t, \min}.$$

For p > 1,

$$\frac{\partial \rho_{\Delta t}}{\partial p}(p,z) > 0.$$

 $\Rightarrow \rho_{\Delta t,\max}, \rho_{\Delta t,\min} \text{ and } f \text{ are strictly increasing.}$  $f(1) < 0, f(\rho_{\max}) > 0 \Rightarrow \text{ unique } p^*_{\Delta t}.$ 

## Sketch of the proof

Step 2 :  $p_{\Delta t}^*$  is the unique solution of the minimax problem

We can prove that (6) has solutions, which must be in  $(1, p_{max})$ .

- For  $p \in (1, p^*_{\Delta t})$ , a careful investigation leads to

$$\max_{0 \le s \le s_{\mathsf{max}}} |\rho_{\Delta t}(\boldsymbol{\mathcal{p}}, \boldsymbol{s})| = -\rho_{\Delta t, \mathsf{min}}(\boldsymbol{\mathcal{p}}) > -\rho_{\Delta t, \mathsf{min}}(\boldsymbol{\mathcal{p}}_{\Delta t}^*) = \max_{0 \le s \le s_{\mathsf{max}}} |\rho_{\Delta t}(\boldsymbol{\mathcal{p}}_{\Delta t}^*, \boldsymbol{s})|.$$

- Similarly, for  $\pmb{p} \in (\pmb{p}^*_{\Delta t}, \pmb{p}_{\mathsf{max}})$ , we obtain

$$\max_{0 \le z \le s_{\max}} |\rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{s})| = \rho_{\Delta t, \max}(\boldsymbol{p}) > \rho_{\Delta t, \max}(\boldsymbol{p}_{\Delta t}^*) = \max_{0 \le s \le s_{\max}} |\rho_{\Delta t}(\boldsymbol{p}_{\Delta t}^*, \boldsymbol{s})|.$$

Therefore,  $p^*_{\Delta t}$  is the unique global minimum of (6).

## Sketch of the proof Step 3 : Asymptotics of $p_{\Delta t}^*$ and $\max_{0 \le s \le s_{max}} |\rho_{\Delta t}(p_{\Delta t}^*, s)|$ with respect to $\Delta t$

We approximate  $\rho_{\Delta t, \max}(p)$  by  $\rho_{\Delta t}(p, 0)$  using

$$|\rho_{\Delta t,\max}(\boldsymbol{p}) - \rho_{\Delta t}(\boldsymbol{p},\mathbf{0})| \leq C \boldsymbol{p}^{-1} \Delta t.$$

 $\Rightarrow$  'approximate' equation

$$\rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{0}) = -\rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{s}_{\max}),$$

whose solution  $p_{\rm eq,\Delta t}^{*}$  can be calculated explicitly and has asymptotic

$$p_{\mathrm{eq},\Delta t}^{*} = \sqrt{2\Delta T \ s_{\max}} \Delta t^{-1/2} + o\left(\Delta t^{-1/2}\right),$$

which implies

$$-\rho_{\Delta t}(\boldsymbol{p}^*_{\mathrm{eq},\Delta t},\boldsymbol{s}_{\max}) = \rho_{\Delta t}(\boldsymbol{p}^*_{\mathrm{eq},\Delta t},0) = 1 - \frac{2\sqrt{2}}{\sqrt{\Delta T \, \boldsymbol{s}_{\max}}} \cdot \Delta t^{1/2} + o\left(\Delta t^{1/2}\right).$$

### Two parameters case

#### Theorem

For  $\Delta t$  small enough, Problem (6) has a unique solution  $(p_{\Delta t}^*, q_{\Delta t}^*)$ . When  $\Delta t \rightarrow 0$ 

$$p^*_{\Delta t} = p^* + O\left(\Delta t\right), \quad q^*_{\Delta t} = q^* + O\left(\Delta t\right)$$

$$\max_{0 \leq s \leq s_{\max}} \left| \rho_{\Delta t}(\boldsymbol{p}^*_{\Delta t}, \boldsymbol{q}^*_{\Delta t}, \boldsymbol{s}) \right| = \rho^* + O\left(\Delta t\right).$$

where  $p^* \simeq 1.1993$ ,  $q^* \simeq 0.0906$  and  $\rho^* \simeq 0.0755$ .

### Remark

- $(p_{\Delta t}^*, q_{\Delta t}^*)$  and  $\rho_{\Delta t}$  do not converge to corresponding continuous values.
- Similar results as in the parabolic case
  - · · · [Gander-Kwok 16]

## Sketch of the proof

**Step 1** : Minimax problem (5) has solutions  $(p_{\Delta t}^*, q_{\Delta t}^*)$  with  $1 \le p_{\Delta t}^* \le p_{max}$ . In additions, the solution must verify

$$\rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{s} = \boldsymbol{0}) = \rho_{\Delta t}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{s} = \boldsymbol{s}_{\max}).$$

which implies  $q = q_{\Delta t,eq}(p)$ . Denote by  $\rho_{\Delta t,eq}(p,s) = \rho_{\Delta t}(p,q_{\Delta t,eq}(p),s)$ . We solve

$$\min_{1 \le p \le p_{\max}} \max_{0 \le s \le s_{\max}} |\rho_{\Delta t, eq}(\boldsymbol{p}, \boldsymbol{s})|$$

Step 2 : The minimax solution must verify the equation

$$-
ho_{\Delta t,\mathrm{eq}}(oldsymbol{p},oldsymbol{s}=0)=\max_{0\leq oldsymbol{s}\leq oldsymbol{s}_{\mathrm{max}}}
ho_{\Delta t,\mathrm{eq}}(oldsymbol{p},oldsymbol{s})$$

**Step 3** : We calculate the limit version of Equiocisllation system for  $\Delta t \rightarrow 0$ .

## OUTLINE

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- Asymptotic study of the convergence factor

### Numerical Illustrations

5 Conclusion and Perspective

## Optimized Convergence factor with one paramter

- $p_{\Delta t}^*$  and  $\max_{0 \leq s \leq s_{\max}} |
  ho_{\Delta t}(p_{\Delta t}^*,s)|$  calculated numerically
  - For  $\Delta t = 1/160$ : Equiocisllation and  $\max_{0 \le s \le s_{max}} \rho_{\Delta t}(p_{\Delta t}^*, s) \simeq \rho_{\Delta t}(p_{\Delta t}^*, 0)$ .



## Optimized Convergence factor with one paramter



## Optimized Convergence factor with two paramters

• For  $\Delta t = 1/160$ : Triple-Equiocisllation at  $(p_{\Delta t}^*, q_{\Delta t}^*)$ .



## Optimized Convergence factor with two paramters

• Markers : 
$$\left| \rho^* - \max_{0 \le s \le s_{max}} \left| \rho_{\Delta t}(p^*_{\Delta t}, q^*_{\Delta t}, s) \right| \right|$$
. Dash lines: best fit line  $C \Delta t$ 



## Pratical performance

T = 1, r = 1/2,  $\Delta t = 1/160$ ,  $y_{ini} = y_{tar} = 0$ , random initial Robin terms.



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## **Conclusion and Perspective**

### Conlusion

- Asymptotic Analysis in case of Explicit Euler Upwind scheme.
- Numerical illustration for time-dependent advection.

### **Ongoing work**

- Convergence Analysis for other scheme (e.g. Lax-Wendroff).
- Extension to multi-domain.
- Para-Opt for Optimal transport Control.

# Thank you for your attention