# Parallel in Time Algorithms for Multiscale Dynamical Systems using Interpolation and Neural Networks

#### Gopal Yalla Björn Engquist

#### University of Texas at Austin Institute for Computational Engineering and Sciences

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#### Outline

- 1 Parallel in Time Algorithms
- 2 Parareal Algorithm
- 3 Phase-accurate Coarse Solver
- 4 Numerical Examples
- 6 Future Work

# Parallel in Time Algorithms<sup>1</sup>

• Required for massively parallel simulations of systems governed by time-dependent dynamical systems, e.g., molecular dynamics.

• Challenge arises due to causality in time.

<sup>1</sup>Martin J Gander. "50 years of time parallel time integration". In: *Multiple Shooting and Time Domain Decomposition Methods*. Springer, 2015, pp. 69–113.

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Parallel in Time Algorithms

# Parallel in Time Algorithms<sup>1</sup>

Multiple Shooting Methods

2 Domain Decomposition & Waveform Relaxation Methods

3 Multigrid Based Methods



<sup>1</sup>Martin J Gander. "50 years of time parallel time integration". In: *Multiple Shooting and Time Domain Decomposition Methods*. Springer, 2015, pp. 69–113.

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### The Parareal Algorithm

Consider the dynamical system:

$$u'(t) = f(u(t)), \qquad t \in (t_0, t_f)$$
  
 $u(t_0) = u_0$  (1)

Divide the time domain  $(t_0, t_f)$  into N equal subdomains  $\Omega_n = (T_n, T_{n+1})$ .

$$u'_{n}(t) = f(u_{n}(t))$$
  $t \in (T_{n}, T_{n+1})$   
 $u(T_{n}) = U_{n}$  (2)

This is simply a shooting method in time, and it equivalent to solving:

$$\begin{pmatrix} U_0 - u_0 \\ U_1 - \phi_{\Delta T_0}(U_0) \\ \vdots \\ U_{N-1} - \phi_{\Delta T_{N-2}}(U_{N-2})) \end{pmatrix} = 0$$
(3)

where  $\phi_{\Delta T_n}(U_n)$  is solution of (1) with initial condition  $U_n$  after time  $\Delta T_n$ .

# The Parareal Algorithm

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Parareal Algorithm

$$\begin{split} U_0^{k+1} &= u_0 \\ U_n^{k+1} &= \mathcal{G}(U_{n-1}^{k+1}) + \left[ \mathcal{F}(U_{n-1}^k) - \mathcal{G}(U_{n-1}^k) \right] \end{split}$$

- $U_n^k$  is the solution  $u(T_n)$  on the  $k^{th}$  iteration of the algorithm.
- G denotes a coarse solver
- $\mathcal{F}$  denotes a fine solver



Video Source: https://en.wikipedia.org/wiki/Parareal



Efficiency = Iterations for Convergence / Total Number of Steps

Video Source: https://en.wikipedia.org/wiki/Parareal

# Drawbacks of the Parareal Algorithm

For Hamiltonian systems, very high accuracy is required for the coarse solver!<sup>2</sup> A good coarse approximation is needed.



Typical coarse integrators fail to predict phase correctly, leading to blow up of error during correction step with fine solver.

<sup>2</sup>Martin J Gander and Ernst Hairer. "Analysis for parareal algorithms applied to Hamiltonian differential equations". In: *Journal of Computational and Applied Mathematics* 259 (2014), pp. 2–13.

Consider a set of M initial conditions (training points)  $\{u_0^i\}_{i=1}^M$  and a set of M corresponding (target points)  $\{v^i\}_{i=1}^M$  defined by,

$$v^i = \mathcal{F}\left(u_0^i\right) \qquad i = 1, \dots, M$$

The set  $\{u_0^i \to v^i\}_{i=1}^M$  acts as a type of look-up table for future initials conditions<sup>3</sup>.

#### Definition

Define a phase plane map  $\mathcal{G}^{map}(\left\{u_0^i \to v^i\right\}_{i=1}^M, U_n)$  to be a coarse solver that uses the information contained in  $\left\{u_0^i \to v^i\right\}_{i=1}^M$  and a point  $U_n$  at time  $T_n$ , to determine the solution  $U_{n+1}$  at time  $T_{n+1}$ .  $\mathcal{G}^{map}$  can be defined through, e.g., Interpolation or a Neural Network.

<sup>3</sup>Jürg Nievergelt. "Parallel methods for integrating ordinary differential equations". In: *Communications of the ACM* 7.12 (1964), pp. 731–733.

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The computation of  $v^i = \mathcal{F}(u_0^i)$  is embarrassingly parallel.



For autonomous ODEs,  $\mathcal{G}^{map}$  can be applied over each subdomain  $\Omega_n$ . Else, generate  $\{u_j^i \to v^i\}_{i=1}^M$  for each  $\Omega_j$ ,  $j = 0, \ldots, N-1$ .



# Numerical Examples

- Traditional parareal algorithm  $\implies \mathcal{G} = \mathsf{RK4}$  with step size T/N
- Modified parareal algorithm  $\implies \mathcal{G} =$  phase plane map with step size T/N
- For both, the fine solver is an adaptive RK45 solver.
- T = Total Simulation Time.
- N = Number of time-subdomains  $\Omega_n$ .

# Harmonic Oscillator

Consider a simple harmonic oscillator:

$$\dot{x_1} = \frac{1}{\varepsilon} x_2$$
$$\dot{x_2} = \frac{-1}{\varepsilon} x_1$$

with

- $\varepsilon = 0.01$
- T = 70 (1000 revolutions)
- $\mathbf{x}(0) = [-2/9, -2/3]^T$

# Harmonic Oscillator



### Lennard-Jones System

$$r'' = \frac{2}{m}F(r)$$

$$F(r) = -\nabla V(r)$$

$$V(r) = 4\varepsilon \left[ \left(\frac{\sigma}{r}\right)^{12} - \left(\frac{\sigma}{r}\right)^6 \right]$$

- $\varepsilon$  = "well depth"
- $\sigma$  = zero distance
- $r_{\min} = 1.12$



# Lennard-Jones System



$$T = 50$$
  $N = 400$   $\mathbf{r}_0 = [1.2, 0]^T$  M=50



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### High Dimensional Harmonic Oscillator

$$\dot{\mathbf{x}} = \frac{1}{\varepsilon} A \mathbf{x}$$

where  $x = [x_1, v_1, x_2, v_2, x_3, v_3, x_4, v_4]^T$ ,  $\varepsilon = 0.01$ , and  $A \in \mathbb{R}^{8 \times 8}$  is defined as,

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\*Neural network defined with logistic activation function, size  $1000 \times 1$ , with a limited memory BFGS solver for optimization.

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# Localized Multiscale Problem

- Type A: Problems that contain local defects or singularities. Microscale model needed only near defects.
- 2 Type B: Microscale model needed everywhere as a supplement to macroscale model, e.g., resolve constitutive model.<sup>4</sup>.

Type A Example: An N-body Problem:

$$m_i \mathbf{\ddot{q}}_i = \sum_{j \neq i}^n \frac{m_i m_j (\mathbf{q}_j - \mathbf{q}_i)}{\|\mathbf{q}_j - \mathbf{q}_i\|^3}$$

- $m_i$  denotes the mass of the  $i^{th}$  body.
- $\mathbf{q}_i$  denotes the position of the  $i^{\text{th}}$  body.

Let n = 2 and assume  $m_2 >> m_1$ .

<sup>4</sup>Weinan E. *Principles of multiscale modeling*. Cambridge University Press, 2011. Yalla & Engquist Parallel in Time Algorithms April 17, 2018

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Apply a traditional parareal algorithm with

- ightarrow RK45 as fine scale solver with adaptive step size.
- $\rightarrow$  RK4 as coarse solver with step size T/N.



# **Conclusion & Future Work**

- Parallel in time algorithms needed for massively parallel simulations of time dependent dynamical systems.
- Results for parareal + phase plane map show promise. Demonstrate a proof of concept.
- Future Work
  - Potential Improvements include use of modern sparse grid and adaptive methods for interpolation or optimizing neural network approach.
  - ► More realistic examples in the realm of molecular dynamics.
  - Scaling/speedup results on modern supercomputing platforms.

# References

- Weinan E. *Principles of multiscale modeling*. Cambridge University Press, 2011.
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\*Code will be available at https://github.com/gyalla/interpareal