44th Woudschoten conference

One-minute poster session

14:15-15:00 Line up in alphabetical order
Error estimation in Model Order Reduction of Parametric Systems

M.H. Abbasi, L. Lapichino, B. Besselink, W. Schilders, N. van de Wouw

Computation time of virtual hydraulic simulator > Sensor sampling time

Is the decomposition always feasible?
Is small-gain condition always satisfied?
Are there any empirical error estimates?
Model Order Reduction for problems with moving discontinuities

H. Bansal, L. Iapichino, S. Rave, W.H.A. Schilders, N. van de Wouw

Applications:
- Nuclear Engineering
- Drilling
- ...

Convection Dominated Problems
Features:
- Stationary or moving discontinuities
- Collision/Interaction of moving fronts

Conventional Reduced Order Modelling Technique
Gibbs Phenomenon and Slow decay of Kolmogorov N-width!

Alternative Reduced Order Modelling Technique:
(Modified) Method of Freezing + Reduced Basis Approximations
Can we extend the combined approach of (modified) method of freezing and reduced basis approximations to deal with non-linear wavefront interactions and merging fronts, and consequently obtain (accurate and stable) online efficient reduced-order models?

Visit Poster Number ‘X’ for more details.
Multilevel Monte Carlo Methods for Geotechnical Engineering

**Situation:** You are performing excavation works

**Goal:** Assess the stability of the slope which contains an uncertain parameter

**Constraint:** Time (= Money)

**Solution:**

**MLMC:**
\[
E[P_L] = \frac{1}{N_0} \sum_{n=1}^{N_0} P_0(\omega^{(n)}) + \sum_{\ell=1}^{L} \left\{ \frac{1}{N_\ell} \sum_{n=1}^{N_\ell} \left( P_\ell(\omega^{(n)}) - P_{\ell-1}(\omega^{(n)}) \right) \right\}
\]

**MLQMC:**
\[
E[P_L] = \frac{1}{R_0} \sum_{i=1}^{R_0} \frac{1}{N_0} \sum_{n=1}^{N_0} P_0(x_{i,n}) + \sum_{\ell=1}^{L} \frac{1}{R_\ell} \sum_{i=1}^{R_\ell} \left\{ \frac{1}{N_\ell} \sum_{n=1}^{N_\ell} \left( P_\ell(x_{i,n}) - P_{\ell-1}(x_{i,n}) \right) \right\}
\]
Machine Learning for Closure Models in Two-Phase Pipe Flow

High fidelity model
• 2D one-fluid model with VOF.

Neural network
\[
\tau_L, \tau_G, \tau_{\text{int}} = f(h_{\text{int}}, u_L, u_G, \rho_L, \rho_G, \mu_L, \mu_G, H, \frac{\partial h_{\text{int}}}{\partial s})
\]

Low fidelity model
• 1D two-fluid model.
Reflection computation of a finite 1D photonic crystal using Bloch modes

L. J. Corbijn van Willenswaard
University of Twente
Reduced SGS models
Positive streamer simulations with different electron attachment rates using the Afivo framework

Hani Francisco\textsuperscript{1}, Behnaz Bagheri\textsuperscript{1}, Jannis Teunissen\textsuperscript{1,2}, Ute Ebert\textsuperscript{1,3}

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\textsuperscript{2}Centre for Mathematical Plasma-Astrophysics, KU Leuven, Belgium
\textsuperscript{3}Eindhoven University of Technology, The Netherlands

\textbf{Framework includes:}
Quadtree adaptive mesh refinement
Multigrid Poisson solver
OpenMP Parallelism

\[\begin{array}{c|cccc}
E \, [\text{KV/cm}] & 15.0 & 11.25 & 7.5 & 3.75 \\
\hline
n_i - n_e [\times 10^{19} \text{m}^{-3}] & 5.2 & 3.9 & 2.6 & 1.3
\end{array}\]
Improving Real-time Quasi-3D Computed Tomography (CT) by Deep-Learned Motion Estimation Filtering

Adriaan Graas, Jan-Willem Buurlage, Felix Lucka

1. Collect projections $Y_t$ with X-rays
2. From projections solve reconstructions in Quasi-3D
   $x_i = R^i_{\text{slice}}(f \ast y_i)$
3. Estimate motion fields in-between the two previous timesteps
4. Predict time $t$ by extrapolating $t-1$ along the motion
5. Warp

Filter

Parallel process 1
Parallel process 2
A multilevel hybrid discretization for Finite Element Methods

Varun Jain

- A *n*-hybrid method
- You first solve for domain interfaces
- Followed by, sub-elements within a macro-element
- Then internal degrees of freedom within an element

- IMPORTANT !!!
  You do not loose any fine scale information
Agent-based Mathematical Modeling of Pancreatic Cancer Growth and Therapies

J. Chen, D. Weihs, and F. J. Vermolen

Cell-based models
- Cell migration
- Cancer metastasis
- Drug-oriented therapy

Cellular Automata
- Cancer progression
- Immune reponse
- Oncolytic virotherapy

Monte Carlo simulations
- Data analysis
- Correlations
- Prediction
A Convex Program for Binary Tomography

Ajinkya Kadu and Tristan Van Leeuwen
Utrecht University, the Netherlands

Find a binary solution(s) from tomoigraphic projections (row and column sums)

Find \( x \in \{0, 1\}^n \) subject to \( y = Ax \)
Fast, robust power flow computations on integrated Transmission-Distribution grids

“In 2030, 70% of generated energy is from renewable resources”

-- the Dutch Climate Agreement

Our research investigates grid stability within these changing conditions

M. Kootte, B. Sereeter, C. Vuik

TU Delft
Numerical computation of the light confinement in realistic 3D cavity superlattices

Marek Kozon\textsuperscript{1,2}, Sjoerd A. Hack\textsuperscript{1,2}, Jaap J.W. van der Veg\textsuperscript{2}, Ad Lagendijk\textsuperscript{1}, and Willem L. Vos\textsuperscript{1}

\textsuperscript{1} Complex Photonic Systems (COPS), MESA+, University of Twente, Enschede, The Netherlands
\textsuperscript{2} Mathematics of Computational Science (MACS), MESA+, University of Twente, Enschede, The Netherlands

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Geometry is the knowledge of eternally existent.
- Pythagoras

Discontinuous Galerkin Finite Element method for port-Hamiltonian system
Nishant Kumar, Jaap van der Vegt and Hans Zwart
Deep learning in low-field MRI
Joint image reconstruction and field map estimation

Merel de Leeuw den Bouter, Martin van Gijzen, Rob Remis
Error Analysis of Mixed Discontinuous Galerkin Discretization of the Maxwell Equations

Kaifang Liu¹, J.J.W. van der Vegt¹, Dietmar Gallistl², Matthias Schlottbom¹

¹ University of Twente, ² Friedrich-Schiller-Universität Jena
A machine learning method for fast model calibration

Shuaiqiang Liu, A. Borovykh, L.A. Grzelak, C.W. Oosterlee

Model calibration:

\[ \text{argmin} \ J(\Theta), \quad \Theta \text{ parameters of math models.} \]
\[ \Theta \in \mathbb{R}^m \]

Supervised learning:

\[ \text{argmin} \ L(\theta), \quad \theta \text{ weights of hidden neurons.} \]
\[ \theta \in \mathbb{R}^M \]

Calibration Neural Networks (CaNN) can do ...
Adjoint-based PDE-constrained optimization with particles

Particles $\leftrightarrow$ Distribution

$k - 1$ $\quad$ forward $\quad$ adjoint $\quad$ $k$ $\quad$ forward $\quad$ adjoint $\quad$ $k + 1$

L. Vanroye, E. Løvbak, G. Samaey, S. Vandewalle

KU LEUVEN  NUMA
Semi-Implicit Time Integrations for the Navier-Stokes-Korteweg Equations

Xiangyi Meng, J.J.W. van der Vegt, Yan Xu

University of Twente & University of Science and Technology of China
Semi-intrusive Uncertainty Quantification for an In-stent Restenosis Model

Anna Nikishova¹, Dongwei Ye¹, Lourens Veen², Pavel Zun³, Alfon Hoekstra¹
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¹Computational Science Lab, University of Amsterdam, ²Netherlands eScience Center, ³ITMO University, Saint Petersburg, Russia

Abstract

Semi-intrusive uncertainty quantification is applied to efficiently analyse uncertainty in the result of a two-dimensional in-stent restenosis multiscale model (ISR2D). In the method, the surrogates based on Gaussian process and Convolutional Neural network substitute the expensive blood flow simulation model.

In-stent Restenosis model

The ISR2D model is a two-dimensional simulation of the post-stenting healing response of an artery.

Blood flow model surrogates

Gaussian process

The function of the flow geometry that predicts the wall shear stress (WSS) is expected to be highly nonlinear. Therefore, the Matérn kernel with smoothness parameter \( \nu = \frac{1}{2} \) which offers piece-wise prediction to cope with potential fluctuation, was chosen.

Convolutional neural network

The shape encoding layers extract the features of the geometry to the shape code. A fully connected layer maps the shape code together with the blood flow velocity to the stress code. The stress decoding part is responsible for a mapping from the stress code to the WSS.

Results

Both GP and NN surrogate models approximate well the wall shear stress for the micro model and significantly reduce the computational cost of UQ (about 6 and 7 times).

References

DSA preconditioned source iteration for a DGFEM method for radiative transfer equation

\[ s \cdot \nabla \phi(x, s) + \sigma_t(x)\phi(x, s) = \sigma_s(x)K\phi + q(x, s) \]

(left: http://www.funnyism.com/i/funnypics/photonadventures-1;
right: https://slideplayer.com/slide/3866488/)

Olena Palii, University of Twente, 9-11 of October 2019
Intrusive Polynomial Chaos for CFD using OpenFOAM

Jigar Parekh, Roel Verstappen

Bernoulli Institute, University of Groningen, Netherlands

\[ \int \phi_i(q)\phi_j(q)\rho_Q(q)dq = \gamma_i \delta_{ij} \]

\[ Y = f(x, q) = \sum_{i=0}^{\infty} f_i(x)\phi_i(q) \]

\[ \mu = f_0, \quad \sigma^2 = \sum_{i=1}^{\infty} f_i^2 \phi_i^2 \]

\[ \rho_Q \quad \text{Input PDF} \]

\[ Y \]

\[ \mu, \sigma \]

\[ \rho_Y \quad \text{Output PDF} \]

https://github.com/parallelwindfarms/gPCPimpleFoam
Numerical Modelling of Contact Discontinuities for the Simulation of Breaking Wave Impacts

Problem:
For convection dominated two-phase flow, interface boundary layers are often very thin compared to relevant interface length scales.

Proposed solution:
- Allow contact discontinuity to develop
  \[ [u_\tau] = \tau \cdot (u^0 - u^l) \neq 0 \]
- Using a new jump condition on the gradient operator
  \[ \left[ \frac{1}{\rho} \partial_\eta p \right] = -\eta \cdot \left[ \frac{Du}{Dt} \right] \]

Ronald Remmerswaal & Arthur Veldman
Low rank approximations to high dimensional diffusion dominated PDEs

Semi-discretization of the heat equation leads to a system of ODEs:

\[
\frac{d\mathbf{u}(t)}{dt} = \dot{\mathbf{u}}(t) = L\mathbf{u}(t).
\]  (1)

Given a time dependent low rank tensor \( \mathbf{A}(t) \in \mathbb{R}^{M \times \cdots \times M} \) and a linear differential operator \( L \) s.t. \( \dot{\mathbf{A}}(t) = L\mathbf{A}(t) \).

Can we factorize \( \mathbf{A}(t) \) and find efficient evolution equations for its factors?

- 2D: \( \mathbf{A} = \mathbf{USV}^\top \)
- nD: \( \mathbf{A} = \mathbf{G} \times_1 \mathbf{U}_1 \times \cdots \times_d \mathbf{U}_d \)
Boundary control of finite volume-based POD-Galerkin reduced order models for buoyancy-driven flows

*Kelbij Star*
Efficient p-multigrid solvers for Isogeometric Analysis

Gauss-Seidel (p=4)

ILUT (p=4)

OLD

NEW

R. Tielen, M. Möller and C. Vuik

Delft Institute of Applied Mathematics, TU Delft
Positivity Preserving Higher Order Numerical Discretizations for Euler Equation

Fengna Yan,
University of Science and Technology of China & University of Twente
J.J.W. van der Vegt, Yan Xu, Yinhua Xia
MATHWARE VOOR HARDWARE EN SOFTWARE

SIoux Lime
Source of your technology

Timo & Keith
and 41 more
A challenging environment for scientific software engineers, applied mathematicians and data scientists

Work on the heavy-duty computational software of mostly corporate customers, both from our office and at the customers’ office

Wide range of application domains

Offices in Delft, 25 colleagues
PhDays 2018