

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.Iapichino, B. Besselink, W. Schilders, N. van de Wouw





TU/e Technische Universiteit Eindhoven University of Technology

Where innovation starts





Model Order Reduction for problems with moving discontinuities

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



Where innovation starts

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 Geothechnical Engineering

Situation: You are performing excavation works



Source: Schijnbare cohesie van onverzadigde gronden - Geotechniek - Januari 2011

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

Constraint: Time (= Money)





Source: https://www.scratchexchange.com/about/

Solution:

KU LEUVEN

$$\begin{split} & \text{MLMC:} \qquad \mathbb{E}[P_L] = \frac{1}{N_0} \sum_{i=1}^{N_0} P_0(\omega^{(n)}) + \sum_{\ell=1}^{L} \left\{ \frac{1}{N_\ell} \sum_{n=1}^{N_\ell} \left(P_\ell(\omega^{(n)}) - P_{\ell-1}(\omega^{(n)}) \right) \right\} \\ & \text{MLQMC:} \qquad \mathbb{E}[P_L] = \frac{1}{R_0} \sum_{i=1}^{R_0} \frac{1}{N_0} \sum_{n=1}^{N_0} P_0(\mathbf{x}_{i,n}) + \sum_{\ell=1}^{L} \frac{1}{R_\ell} \sum_{i=1}^{R_\ell} \left\{ \frac{1}{N_\ell} \sum_{n=1}^{N_\ell} \left(P_\ell(\mathbf{x}_{i,n}) - P_{\ell-1}(\mathbf{x}_{i,n}) \right) \right\} \end{split}$$

Machine Learning for Closure Models in Two-Phase Pipe Flow

High fidelity model

• 2D one-fluid model with VOF.

Neural network

 $\tau_L, \tau_G, \tau_{\rm int} =$

 $f(h_{\text{int}}, u_L, u_G, \rho_L, \rho_G, \mu_L, \mu_G, H, \frac{\partial h_{\text{int}}}{\partial s})$

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 Francisco¹, Behnaz Bagheri¹, Jannis Teunissen^{1,2}, Ute Ebert^{1,3}





Framework includes: Quadtree adaptive mesh refinement Multigrid Poisson solver OpenMP Parallelism

¹Centrum Wiskunde & Informatica, Amsterdam, The Netherlands ²Centre for Mathematical Plasma-Astrophysics, KU Leuven, Belgium ³Eindhoven University of Technology, The Netherlands



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Science and Innovation With Thunderstorms

H2020 Marie Skłodowska-Curie Innovative Training Networks

Improving Real-time Quasi-3D Computed Tomography (CT)

by Deep-Learned Motion Estimation Filtering

Adriaan Graas, Jan-Willem Buurlage, Felix Lucka



A multilevel hybrid discretization for Finite Element Methods

Varun Jain



• A *n*-hybrid method

Delft

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

(2019, S. Luesutthiviboon)

• 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 TOMOGRAPHIC **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



Numerical computation of the light confinement in realistic 3D cavity superlattices <u>Marek Kozon^{1,2}</u>, Sjoerd A. Hack^{1,2}, Jaap J.W. van der Vegt², Ad Lagendijk¹, and Willem L. Vos¹

¹ Complex Photonic Systems (COPS), MESA+, University of Twente, Enschede, The Netherlands ² Mathematics of Computational Science (MACS), MESA+, University of Twente, Enschede, The Netherlands e-mail: <u>m.kozon@utwente.nl</u>

UNIVERSITY OF TWENTE.

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



ŤUDelft

Global Initiative







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:

 $\underset{\Theta \in \mathbb{R}^m}{\operatorname{argmin}} J(\Theta), \Theta \text{ parameters of math models.}$

Supervised learning:

 $\underset{\boldsymbol{\theta} \in \mathbb{R}^{M}}{\operatorname{argmin}} L(\boldsymbol{\theta}), \boldsymbol{\theta} \text{ weights of hidden neurons.}$

Calibration Neural Networks (CaNN) can do ...





Adjoint-based PDE-constrained optimization with particles

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









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

for $i \leq N$

SMC

BF metamodel



UNIVERSITEIT VAN AMSTERDAM

Anna Nikishova¹, Dongwei Ye¹, Lourens Veen², Pavel Zun^{1,3}, Alfons Hoekstra¹ A.Nikishova@UvA.nl, D.Ye@UvA.nl

Abstract

Semi-intrusive uncertainty quantification is applied to efficiently analyse uncertainty in the result of a two-dimensional in-stent restenosis multiscale model (ISR2D) [1]. 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.



Uncertainty in the ISR2D response is due to the model stochasticity and uncertainty in the model parameters [2]:

- inlet blood flow velocity at $0.48 \pm 10 \text{ m/s}$,
- maximum deployment depth at 0.11 \pm 0.02 mm,
- endothelium regeneration time at 19 ± 4 days.

Semi-intrusive Metamodeling

[3].



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.



The SI method involves replacing a computationally expensive single-scale submodel with a surrogate

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) [4].





Fig. 4: Inputs of Gaussian process regression



Fig. 5: The CNN model: shape encoding, nonlinear mapping and stress decoding.

References

- Dec 2018.

Results





[1] H. Tahir, C. Bona-Casas, and A. G. Hoekstra, "Modelling the effect of a functional endothelium" on the development of in-stent restenosis," PLoS One, vol. 8, no. 6, p. e66138, 2013.

[2] A. Nikishova, L. Veen, P. Zun, and A. G. Hoekstra, "Uncertainty quantification of a multiscale model for in-stent restenosis," Cardiovascular Engineering and Technology, vol. 9, pp. 761–774,

[3] A. Nikishova and A. G. Hoekstra, "Semi-intrusive uncertainty propagation for multiscale models," Journal of Computational Science, vol. 35, pp. 80 – 90, 2019.

[4] D. Ye, A. Nikishova, L. Veen, P. Zun, and A. G. Hoekstra, "Surrogate modelling with Gaussian process and Neural network for an in-stent restensis model in semi-intrusive uncertainty quantification," Submitted to Reliability Engineering & Systems Safety, 2019.

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

$$\mathbf{s} \cdot
abla \phi(\mathbf{x}, \mathbf{s}) + \sigma_{\mathbf{t}}(\mathbf{x}) \phi(\mathbf{x}, \mathbf{s}) = \sigma_{\mathbf{s}}(\mathbf{x}) \mathbf{K} \phi + \mathbf{q}(\mathbf{x}, \mathbf{s})$$







Photon self-identity problems.

"NO, I'M TRAVELLING LIGHT."

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



university of

groningen

https://github.com/parallelwindfarms/gPCP impleFoam

Numerical Modelling of Contact Discontinuities for the Simulation of Breaking Wave Impacts

Proposed solution:

Allow contact discontinuity to develop

 $\llbracket u_{\tau} \rrbracket = \boldsymbol{\tau} \cdot (\mathbf{u}^{g} - \mathbf{u}^{l}) \neq 0$

 Using a new jump condition on the gradient operator

$$\left[\!\left[\frac{1}{
ho}\partial_{\eta}p
ight]\!\right] = -\boldsymbol{\eta}\cdot\left[\!\left[\frac{D\mathbf{u}}{Dt}
ight]\!\right]$$



Ronald Remmerswaal & Arthur Veldman

Problem:

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



Low rank approximations to high dimensional diffusion dominated PDEs

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

$$\frac{\mathrm{d}\boldsymbol{u}}{\mathrm{d}t}(t) = \dot{\boldsymbol{u}}(t) = L\boldsymbol{u}(t). \tag{1}$$

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

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

▶ 2D: A = USV^T

$$\blacktriangleright nD: \mathcal{A} = \mathcal{G} \times_1 \mathcal{U}_1 \times \cdots \times_d \mathcal{U}_d$$





Jacob Snoeijer



Boundary control of finite volume-based POD-Galerkin reduced order models for buoyancy-driven flows *Kelbij Star*





Efficient p-multigrid solvers for Isogeometric Analysis



OLD



R.Tielen, M. Möller and C. Vuik

Delft Institute of Applied Mathematics, TU Delft

TUDelft





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





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Timo & Keith and 41 more



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