



GCCE PostDoc-Meeting 28.02.2023 , 9:00–12:00 at BMTEG138 Biomechanics Building, ground floor, Stremayrgasse 16, 8010 Graz

1. Opening speech and moderation Ceyhun Özdemir $\leq 1-2 \min ; 9:00$

2. Presentation of Vahid Badeli 9:00-9:30

 $\underline{\mathbf{Title:}}$ Multiphysical simulation of flow-related impedance changes in arteries

Abstract/Motivation: Bioimpedance methods, such as impedance cardiography (ICG) and impedance plethysmography (IPG), provide a non-invasive, time-continuous, cheap, and convenient technology for determining cardio-dynamic parameters. A lack of and difficult accessibility to data obstructed the improvement of signal interpretability and parameter estimation accuracy hence widespread clinical adoption. The limitations mentioned above need to be overcome with multi-physical simulations of different scenarios.

3. Presentation of Dino Zrnic 9:30-10:00

 $\underline{\mathbf{Title:}}$ The importance of inflow boundary conditions for blood flow simulations in the human aorta

Abstract/Motivation: Cardiovascular diseases are the most common causes of human death worldwide [1]. Typical life-threatening cardiovascular diseases are a ortic dissection (AD) and ascending thoracic aortic aneurysm (ATAA). The former is initiated by a rupture and delamination of tissue layers in the aortic wall [2]. The latter is identified with an abnormal bulging and weakening of the ascending thoracic aorta wall [3]. It is widely known that the wall tissue remains healthy only for a certain range of the mechanical load acting on the aorta wall due to blood flow. The mechanical load is due to pressure and viscous stress. Blood flow thorugh the aorta is displacement driven due to the action of the heart. It is by nature an unsteady flow of a non-Newtonian, shear-thinning liquid thorugh a curved vessel [4]. The respective contributions to the aorta wall stress are analysed with numerical simulations. The simulation results must accurately mimic the hemodynamic environment within the aorta, which makes the choice of the inlet velocity profile (IVP) crucial [5]. However, the availability in vivo measurement data is limited, and researchers are still inclined to use idealised IVPs. These greatly idealised IVPs are often axisymmetric with the maximum velocity position (MVP) on the symmetric axis of the aorta, i.e. in the center of the inlet cross-section.

Our idea is to analytically generate IVPs, which are time dependent, adjusting its volume flow rate with patient-specific data extracted from the time-resolved 3D phase contrast magnetic resonance scans of healthy subjects [6]. The generated IVP is asymmetrical with a user-defined MVP, which makes the velocity profile more realistic. For every simulation cases, the MVP is fixed in time. Among the simulation cases, the MVP is placed at positions with different radial and polar angular coordinates in the aorta inlet cross-section. We aim to quantify the MVP influence on the cycle-average wall shear stress and pressure profiles on the aorta wall. With the MVP variation, we will identify regions where values of the mechanical load exceed a healthy range. For the cases with exceeding values, we will quantify the contributions of the primary flow, and of the secondary flow [7] due to curved geometry. Patients in an early stage of AD and ATAA, as well as surgeons replacing aortic valves, will benefit from the conclusions from the present work.

4. Coffee break 10:00-10:30

5. Presentation of Jan Tibaut 10:30-11:00

<u>**Title:**</u> Investigation of the red clay brick heat transfer coefficient

Abstract/Motivation: There is a need for the development of materials that can store heat. Heat energy is used in different ways, e.g. for house warming or production of electricity from solar power plants. However, to use the heat energy efficiently isolating materials are needed. There are different materials available to isolate houses and storage containers. Some of those materials are expensive and over engineered. The best available material for isolation of heat would be air, that has the thermal coefficient $\lambda_{air} = 0.02446 \frac{W}{mK}$. However, transparent walls that would allow air flow are not optimal. An alternative are red clay bricks, because red clay is a natural product that is present everywhere on the planet. But the thermal coefficient of red clay bricks is high $\lambda_{air} = 0.6 \frac{W}{mK}$. To reduce the thermal coefficient cavities of air can be added in the brick.

For the simulation of fluid flow the non-dimensional velocity-vorticity formulation of the Navier-Stokes equations is applied. These equations are reformulated into the Yukawa equation by approximating the time derivative by finite differences. The corresponding BDIM has been accelerated with the \mathcal{H}^2 -methodology. It is considered that the laminar fluid flow is present in the cavities. Thus, the Rayleigh number is below 10⁶. Numerical studies will be presented.

6. Presentation of Christopher Albert 11:00-11:30 Title: Physics-Consistent Gaussian Regression

Abstract/Motivation: This is an introduction to a regression method to construct physical scalar and vector fields from point measurements. The approach is based on Gaussian processes with specialized kernels. Based on the underlying linearity property, such kernels exactly fulfill source-free laws of physics in the form of linear differential equations. Examples are acoustics and electromagnetic equations. Point sources are added by linear superposition of fundamental solutions. Source strength and location can be inferred during regression and hyperparameter optimization. For details, see [8].

7. Presentation of Sascha Ranftl 11:30-12:00

<u>**Title:**</u> Neural networks as Gaussian processes for differential equations

Abstract/Motivation: We will consider a mathematical connection between three ' realms ' or notions, namely physics in the form of differential equations, probability theory in the form of (Gaussian) stochastic processes and machine learning in the form of neural networks [9]. For this we make use of two basic findings:

- 1) neural networks can be interpreted as Gaussian stochastic processes under reasonably general and practical conditions
- 2) stochastic processes can often be described via differential equations and vice versa

Both together allow us to construct neural networks and Gaussian process kernels constrained a priori by differential equations. Comparisons to standard approaches of 'physics-informed learning', that is weak constraints a posteriori, will be discussed. While machine learning approaches to differential equations may not compete with e.g. highly developed FEM solvers in standard settings, they certainly are useful for problems which are difficult with traditional solvers alone. In particular, we are motivated by many-query problems that require a large number of calls to the solver, such as uncertainty quantification, optimization or inverse problems, e.g. model selection and calibration, data assimilation etc. Learned models can then be convenient. If time permits, sich examples will be discussed.

8. Ending $\approx 12:00$

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