Stefano Cassola, Tim Schmidt, Miro Duhovic, David May

Leibniz-Institut für Verbundwerkstoffe GmbH, Erwin-Schroedinger-Strasse 58, Kaiserslautern, Germany Email: <u>stefano.cassola@ivw.uni-kl.de</u>

Keywords: Flow field prediction, microstructure, convolutional neural networks

Abstract

For the design of robust Liquid Composite Molding processes the determination of the textile permeability on various spatial scales is essential. In recent years researchers started to explore the potential of numerical methods for the virtual permeability prediction and numerous studies have adressed the possibilities and limitations of such approaches. In this context numerical methods such as the Finite Volume, the Finite Element or the Lattice Boltzman Method are used to iteratively solve the Stokes' equation for creeping flow in Statistical Volume Elements (SVE) which is followed by a volume averaging of the flow velocity and the use of Darcy's law to calculate the permeability. For the determination of the full permeability tensor this process has to be repeated three times solving for the steady state velocity field under a pressure gradient in each principle direction. Recent studies showed that microscale SVEs have to contain around 400 fibres, the domain resolution needs to be sufficiently large (around 10 voxels per fiber) and the permeability calculation should be perfored in 3D domains in order to obtain permeability values that are statistically representative [1, 2]. Hence, virtual permeability prediction involves multiple intensive computations on large computational domains in order to produce meaningful, high quality results for fibrous microstructures. In this study, we use deep learning to predict the flow velocity field in large, 3D fibrous microstructures ($\geq 160^3$ voxels) in order to speedup the permeability calculation and maintain a high level of interpretability. The network architecture, called MS-Net, was proposed by Santos et al. [3] and is based on coupled 3D convolutional neural networks (3D-CNN) specifically designed for the use case of velocity field prediction in porous media.

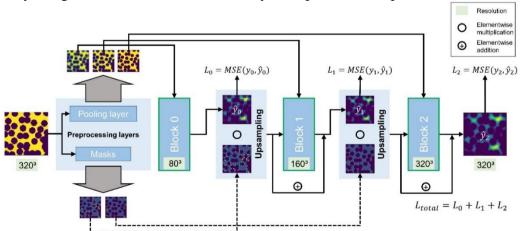


Figure 1: MS-Net architecture used for the initial training trials

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MS-Net uses a hierarchical network structure in which the relationship of porous structures and the velocity response is learned on various resolutions of the same computational domain. Overall, this leads to efficient computations since coarse resolutions can provide valuable information to the network at minimal computational cost. To assess the hardware requirements and the computational effort, training on a small databset of only 8 data points was conducted. The training of 1000 epochs took 24h while around 22 GB of the GPU memory was needed. The inference (prediction) time was around 5 seconds. Considering the low amount of data that was used for the training (eight samples), the results show promising predictions for the flow field, especially for flow parallel to the fiber direction with an error of only 0.3% on the mean velocity. Furthermore, the patterns of high and low velocity areas are well captured by the neural network. Due to the higher homogeneity of the flow field in the transverse fiber direction, learning an accurate representation of the flow field becomes more challenging. Hence, the error increases to 44.3% on the mean velocity.

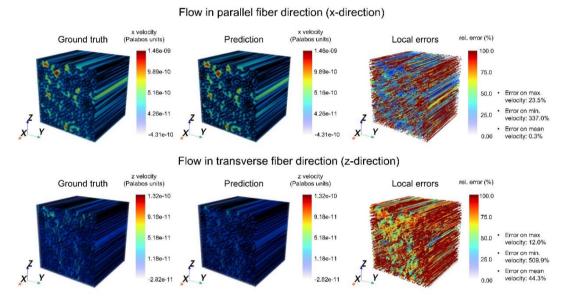


Figure 2: Flow field prediction of a fibrous microstrcutre with a resolution of 320³ voxels

In our work we also aim to tailor the network design using the latest advances in deep learning for an optimal performance on our dataset consisting of 4284 voxelized, synthetic, 3D geometries and flow velocity fields with an original resolution of 320³ voxels varying in fiber volume content, fiber diameter and fiber direction. For the purpose of quicker hyperparameter tuning and experimenting the geometry resolution is downscaled to 160³ and the velocity field is subsequently recalculated. Making use of this synthetic data we can show that a modified MS-Net architecture is a viable option for the flow prediction in large 3D domains which ultimately makes the machine learning based permeability prediction more robust and more interpretable by providing velocity field information.

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