Temperature assimilation for convective flows by convolutional neural networks

M. Mommert [1], C. Bauer [1] and C. Wagner [1,2]

[1] Department Ground Vehicles, Institute of Aerodynamics and Flow Technology, German Aerospace Center (DLR), 37073 Göttingen, Germany
[2] Institute of Thermodynamics and Fluid Mechanics, Technische Universität Ilmenau, 98684 Ilmenau, Germany

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Abstract:
The transport of heat in convective flows plays an important role in nature and in many technical applications. Precise predictions of such convective flows can be made in Direct Numerical Simulations (DNS), which require a substantial amount computing time and storage space. Thus, DNSs can only be used for predictions over comparatively short time periods and for flow problems, which can usually also be investigated in the laboratory due to their dimensions. A canonical laboratory experiment that is well suited for basic investigations of turbulent, thermal convection flows and the development of models is the so-called turbulent Rayleigh-Bénard convection, which occurs as a result of buoyancy forces in cells heated from below and cooled from above with adiabatic side walls.

Compared to the DNS, measurements can capture the velocity field over long periods of time. However, in order to be able to determine the heat transport in convective flows, additional spatial temperature measurements are typically carried out. Respective combined measurements are also very laborious and therefore only applied scarcely. In order to provide an estimated temperature distribution based on precise velocity field measurements, the assimilation of the temperature field from the velocity vector field is pursued. So far, the approach of extracting temperature fields based on the conservation laws has been explored [1]. At the same time, machine learning provides promising tools for regression tasks such as the one at hand [2].

Figure 1 introduces the approach investigated here: As model, a convolutional neural network with an encoder-decoder architecture is defined. It exploits the structural information of the velocity fields and uses order reduction to cope with noisy inputs. Subsequently, this model is trained with clippings of down-sampled data of a DNS conducted over a short time period, with the velocity components as input and temperatures as output. For validation or inference, the generated clips of the temperature field are joined overlapping each other. Thus, the model can be used to predict temperatures making use of velocity fields measured over long time periods.

As an exemplary result of the overlapping reconstruction, figure 2 displays a vertical center plane of the 3-dimensional Rayleigh-Bénard convection sample used as training example. From left to right, a down-sampled DNS velocity vector field and temperature field from the validation data set as well the respective temperature prediction are shown. The comparison of the temperature fields reveals that the prediction is visually well correlated with the DNS results.

At the conference, we will present a comparison of different design choices for the model to provide a base on which more universal and complex models can built.

References

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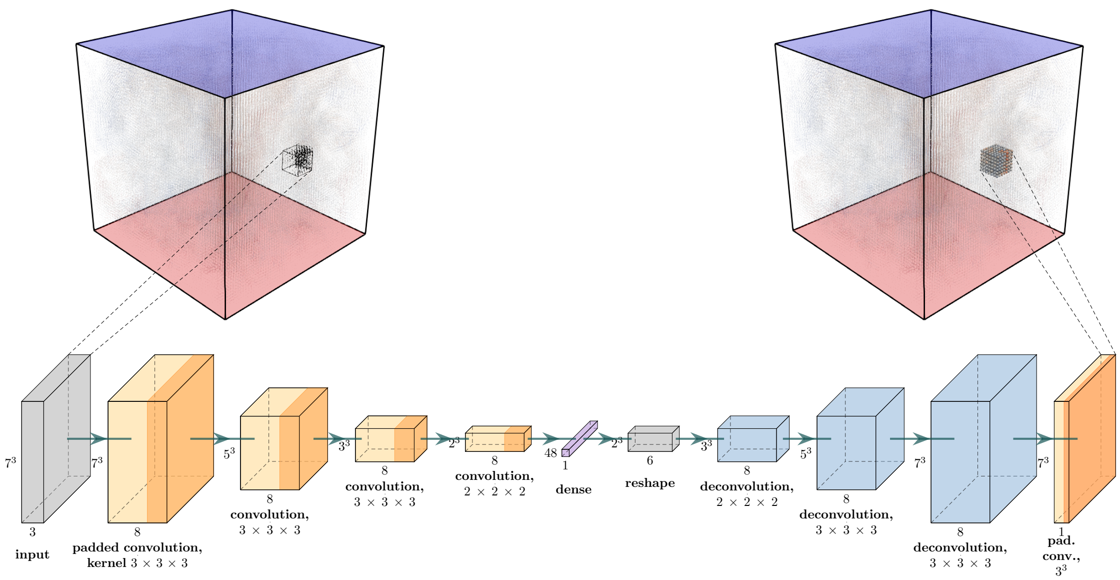

Figure 1: *Architecture of the encoder-decoder neural network, which is fitted to predict temperatures based on velocity information of clippings of the domain (Network visualization with PlotNeuralNet - 10.5281/zenodo.2526396).*

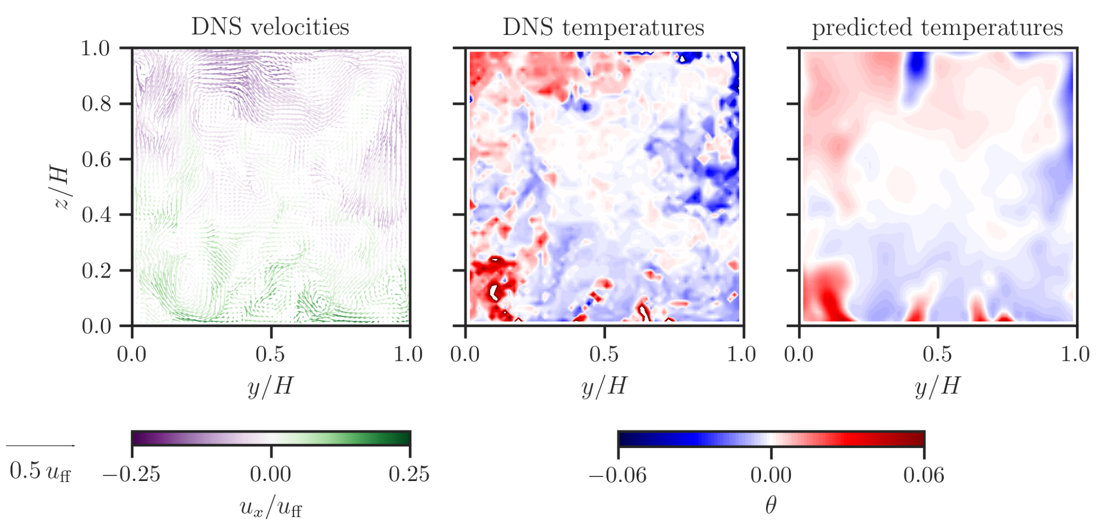

Figure 2: *Instantaneous velocity (left) and temperature (middle) data provided by the downsampled DNS in a central vertical section of the sample compared to the overlapping reconstruction of the temperatures predicted by the neural network (right). The investigated case is characterized by the Rayleigh number* $Ra = 10^{10}$ *and the Prandtl number* $Pr = 6.9$. u_{ff} *indicates the free-fall velocity and* θ *constitutes the dimensionless temperature ranging from* -0.5 *to* 0.5.