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Flow Field Analysis of a Racing Car based on Dimensionality Reduction and Clustering

Michaela Reck [1)] **René Hilhorst** [2)] **Marc Hilbert** [3)] **Thomas Indinger** [1)]

1) Technical University of Munich, Chair of Aerodynamics and Fluid Mechanics
Boltzmannstraße 15, 85748 Garching, Germany (E-mail: michaela.reck@tum.de)
2) TOYOTA GAZOO Racing Europe GmbH
Toyota-Allee 7, 50858 Cologne, Germany
3) LIACS - Leiden University, Niels Bohrweg 1, 2333 CA Leiden, Netherlands

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Efficiently analysing Computational Fluid Dynamics (CFD) simulations of a racing car is key to detect trends in flow topology that cause changes in performance. However, manual analysis of a decent amount of CFD calculations is time consuming and complex. The motivation of this research is to optimize the aerodynamic analysis workflow with the use of a neural network architecture, namely Convolutional Autoencoder (CAE). The target is to detect significant regions in the flow domain that contribute to fluctuations of aerodynamic performance parameters, namely Key Performance Indicators (KPI).

Fig. 1 Toyota prototype racing car.

This research focuses on the examination of the flow field around a Toyota prototype racing car, which is depicted in Fig. 1. Flow fields obtained from Reynolds Averaged Navier Stokes (RANS) simulations serve as input for the CAE. During the training process, the model learns to express dominant flow features in reduced dimensions in an end-to-end unsupervised fashion. The proposed method is compared to traditional Principal Component Analysis (PCA). KMeans clustering is applied to group inherent flow structures into the same cluster. The task is to extract interesting regions that justify trends in performance metrics. The initial dataset is composed of 440 three-dimensional flow fields around the prototype resulting from steady RANS simulations. In this paper, we determine a 2D section from the flow domain, which serves as input for the CAE. The target is to find a representative frame that contributes to great variation in flow topology. Following aerodynamic parameters are considered: Total pressure coefficient static pressure coefficient and vorticity in x-direction.

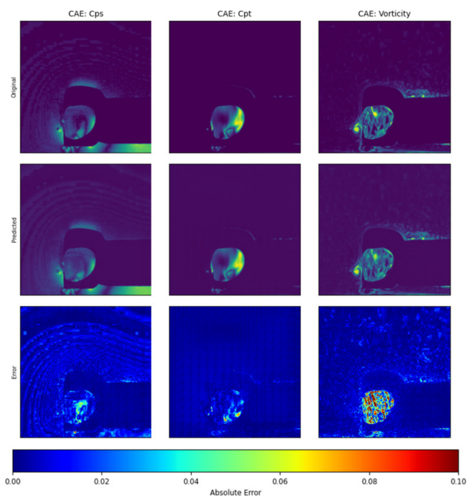

Fig. 2 Absolute prediction error of the CAE

For each aerodynamic parameter, an Autoencoder model is developed. We name this process mixture of CAEs. The approach is to uncover features in the flow learned by the CAE for each aerodynamic parameter, respectively.

A comparison of a selected input frame, its corresponding prediction after passing through the model, and the absolute error between input and output is depicted in Fig 2. After mapping the flow field sections into the low-dimensional embedding, KMeans clustering is applied. With a total number of 4 clusters, the corresponding t-SNE visualization is demonstrated in Fig. 3 (top). The CAE approach is evaluated using the deltas of the total downforce over drag as KPI metric. The latter is labelled with the corresponding clustering results (see Fig. 3 (bottom)). The latent space representation of the CAE is able to detect trends in KPI based on certain type of flow profiles.

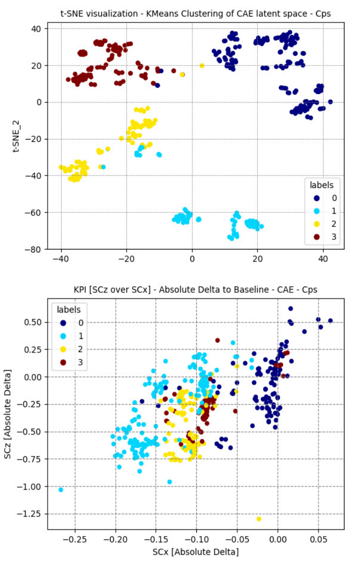

Fig. 3 Clustering result (top) and KPI plot (bottom)