딥 러닝을 사용한 층류 흐름의 CFD 예측

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CFD Prediction of Indoor Airflow using Deep Learning

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Abstract

Energy efficiency and indoor thermal comfort are both significant aspects of the built circumstances, so they must be considered concurrently throughout the design phase of a building. Computational fluid dynamics (CFD) and building energy simulation (BES) can be utilized together to give complementary information on a building's energy performance and the conditions of the internal environment. Nevertheless, the primary deficiency of CFD is its high computational expense, which restricts its function. Deep Learning (DL) is regarded as one of the most practical alternatives to CFD because of its evolved modeling capabilities, high accuracy, and adaptability at the expense of significant computational resources. This study proposes to validate the expediency of using U-Net architecture, a deep learning subfield, to predict indoor airflow based on CFD. The findings demonstrate that the U-Net simulates indoor airflow prediction with a total loss of 0.7688 and a total validation loss of 0.5804. It is confirmed that U-Net can be used to predict indoor airflow.

Keywords: computational fluid dynamics, deep learning, U-Net, airflow prediction

Ⅰ. Introduction

As the energy crisis has deteriorated, the building energy simulation (BES) method has been broadly employed to predict building energy utilization and thermal performance. A year's worth of mechanical system performance and energy consumption data can be thoroughly researched by some BES programs for the target facility [1].

Integrating building energy simulation (BES) and computational fluid dynamics (CFD) delivers essential data about constructing energy and environmental conditions, a valuable tool to manage the issues. This integration between BES and CFD can deliver the necessary data and produce better outcomes than either program working independently. Furthermore, CFD and BES simulation can be deployed simultaneously with one another to find a comprehensive resolution for the operation and design of low-energy buildings [2].

In terms of deep learning techniques applied to CFD, the approach of this study uses the direct calculation of the desired fluid characteristics. The U-Net model used in this study initially modified CNN, which was first implemented in biomedical image segmentation, can localize images by forecasting them pixel by pixel. The network is potent and sufficient to produce precise predictions [3]. In order to predict two-dimensional indoor airflows that CFD first rebuilt, with U-Net model architecture is implemented, as described in this study.

Ⅱ. Methods

A. Geometry Representation

The geometry representation used in this paper is a Signed Distance Function (SDF) provides a distance of point X from a surface's boundary, allowing us to identify whether a point is inside or outside the boundary [4]. In the train and test dataset utilized for this study, there are 300 cases of each Ux, Uy, Grid, and Boundary data, with the target output of Ux and Uy for velocity fields.

B. U-Net Model Architecture

The U-Net architecture comprises an expanded lane on the right and a contracting lane on the left of the architecture. The contracting lane adheres to the standard convolutional network architecture. Each step of the expansive lane is generated after the upslope of the feature map [5]. The primary contribution of U-Net in this study is concatenating more high-resolution feature maps from the decoder side with the upslope elements to enhance the learning of models with subsequent convolutions. Since upslope is a sparse process, a solid prior from earlier stages is required to describe localization more precisely. In U-Net architecture, there are two convolutional layers for each method. The image dimensions are halved when operating the max pooling process. While this design uses padding= "same," the size descending from 200×300 to 196×296 is due to padding problems. On the other side, the image will be enlarged to its initial size on the expansive lane. Transposed convolution is an upslope method that enlarges images. Here, data from the foregoing layers are merged to create a prediction that is more precise. This paper shows how well such Deep Learning of U-Net networks can be utilized to map combined velocity field geometries to steady-state airflow solutions, even though U-Net was first constructed to segment medical images [6].

III. Results and Analysis

In this paper, the U-Net model was trained with a dataset that was split into 70% train and 30% test, the number of epochs 2000, and the learning rate 0.001. The experiment was carried out with 1 batch size, while the Adam optimizer was implemented because it can gain the fastest confluence time[7]. The total loss of 0.7688 and total validation loss of 0.5804 of the training U-Net model. Due to the noise that small batches add to the updates, which benefits training in avoiding suboptimal local minima, it was concluded that the small batch used in this study has a regularizing effect[8].

In Figure 1, the comparison of prediction and target data is shown, along with the magnitude of the Ux and Uy velocities in the airflow field. With relatively low error rates, the U-Net model can represent these modeling processes.

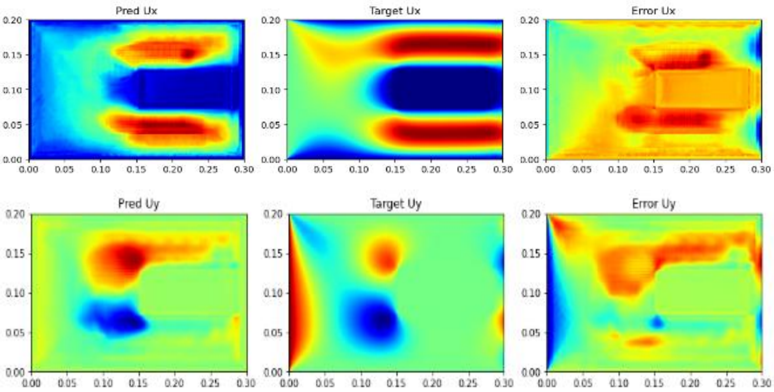

Figure 1. Data prediction, target, and data error for Ux and Uy velocity fields.

III. Conclusion

This study uses a U-Net model, which predicts airflow in a two-dimensional environment of Ux and Uy velocity fields, to demonstrate how indoor airflow prediction based on CFD is implemented. With a total loss of 0.7688 and a validation loss of 0.5804, the U-Net model is proven viable for accurate prediction.

For future work, the study needs to involve predicting pressure fields along with Ux and Uy velocity fields of airflow. Furthermore, the U-Net model can be combined with another model, such as a Transformer, to solve the overfitting and gain lower loss and validation loss.

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