A 3D Convolutional Neural Network Approach for Sustainable Architectural Design through Computational Fluid Dynamics Simulation and Reverse Design Workflow

Abstract

This paper introduces a versatile and flexible approximation model. This model is designed for the near real-time prediction of steady turbulent flow within a 3D environment. The model uses residual Convolutional Neural Networks (CNNs). This methodology provides immediate feedback, enabling real-time iterations during the initial stages of architectural design. Furthermore, this workflow is inverted, offering designers a tool that produces building volumes based on desired wind flow patterns.

1 Introduction

Architectural design is inherently influenced by environmental constraints from its early conceptual stages. During this period, when the forms of buildings and cities are established, informed decisions regarding sustainable development are critically important. However, design proposals can evolve rapidly, making it difficult to provide relevant simulations at a comparable pace. In particular, Computational Fluid Dynamics (CFD) requires intricate geometry preparation and computationally demanding solutions. This process is not only time-consuming but also conflicts with the speed of design iterations. To improve the integration of CFD in design processes, this work concentrates on employing data-driven flow field predictions. It also leverages approximation using CNNs. This approach aims to overcome the challenges associated with traditional CFD simulations and make them more accessible for iterative design processes.

Prior research has shown encouraging outcomes in the rapid simulation of fluid dynamics and in the approximation of the Navier-Stokes equations. We emphasize the use of CNNs with residual blocks in architectural contexts within 3D domains. Additionally, we explore the application of reverse training to forecast architectural volumes. While rapid forward prediction offers considerable potential for improving sustainable design, the process of using CFD analysis results to directly influence design relies on the designer's creativity. There is no straightforward way to inform design choices other than choosing the most effective design among many proposals. We address this by using the same CNN model but trained in the opposite direction.

2 Data Creation and Simulation

Using a visual programming language and standard Computer-Aided Design (CAD) software, several geometries representing urban structure samples were produced. These samples were designed to replicate common variations in building heights within a city. The widths and depths were also confined to typical minimum and maximum dimensions. Each sample is represented as a 3D mesh and has to fit inside a space measuring 256m x 128m x 64m. These meshes are then voxelized with a 1-meter resolution. Our dataset comprised 3500 samples in total: 3325 (95

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In design, analysis and optimization of aerodynamic systems, flow fields are simulated through the use of CFD solvers. However, CFD simulation usually involves intensive computations, requiring considerable memory and time for each iterative step. These limitations of CFD restrict the potential for design exploration and interactive design processes. Our data set was generated by employing OpenFOAM software. To facilitate CNN training, the entire process was automated due to the large number of cases required.

3 Neural Network Architecture

Our network architecture follows a U-net structure. It includes eight encoder layers and seven decoder layers. Each layer integrates a residual block that contains a 3D convolution with stride 2 and 4x4x4 filters, along with a 3D convolution with stride 1 and 3x3x3 filters. According to our tests, these gated blocks improved our results. This was observed when compared to a basic encoder-decoder architecture. We utilized concatenated exponential linear units for activation purposes. This fully connected CNN has excellent generalization properties for geometries beyond those in the training set. It also works well for input data larger than the dimensions of the training samples. This network can approximate wind velocity fields three orders of magnitude faster than a CFD solver in a 3D domain. The test mean squared error loss showed continuous improvement across 1000 epochs for both forward and reverse directions. This demonstrates the generalizability of the approach. In the reverse direction, we adjusted the number of output channels to 1. This represents whether a location is occupied by a building (1) or outside space (0). In contrast, the forward direction has 3 output channels, which represent the x, y, and z components of wind direction vectors.

4 Results

We implemented a Flask server that allows for interactive prediction using the visual programming interface of the common CAD software Rhino. This CAD software offers visualization capabilities that were utilized to generate sample images. We present a sample of forward CFD prediction. This visualizes the wind velocity magnitude (calculated using the Frobenius norm of the x, y, and z components). In addition, we present a reverse prediction of building volumes. Yellow indicates undesirably high wind speed, while blue represents low, preferable wind speed.

5 Discussion

Rapid analysis responses are essential in the early conceptual design stages across multiple industries. The demonstrated effectiveness of near real-time prediction indicates that the proposed methodology has promising potential applications beyond architecture. The reverse approach directs designers to focus on the desired outcome, specifically human well-being. This facilitates more efficient use of time in sustainable design processes. Future research aims to improve the cost function by adding continuity equation error and implementing a generative adversarial network. We are also exploring possibilities for generating multiple building predictions from a single wind flow input.

Supplementary Materials

A Case Study

We present a designer's workflow utilizing our forward and reverse networks. The aim is to design and optimize urban layouts to achieve desired wind flows. This hypothetical site has a bounding box width and depth of 256 meters, with a maximum height of 64 meters. This area is twice the size of our training dataset, showing the benefit of using a CNN.

Our neural network is built with TensorFlow 2.0 and its Keras module. Communication between CAD software and TensorFlow is enabled through HTTP requests which are managed by a Flask server. Currently, the pre-processing of geometry is the bottleneck, as it needs to be voxelized. This can be improved in the future by using external mesh libraries.

A.1 Initial Sketch of Volumes

Initial sketches of urban layouts can be developed in CAD software, providing a visual representation of the desired design and also producing an initial CFD analysis. This initial sketch step can be skipped, allowing a designer to directly create a point cloud of slow-wind areas (as shown in step A.3).

A.2 Initial Interactive CFD Analysis

Our forward-trained network can produce spatial CFD analysis predictions within seconds. This prediction is visualized in our CAD software.

A.3 Thresholded and Modified CFD Analysis

The CFD is filtered to focus only on areas with lower wind speeds. These locations are better suited for outdoor activities. A point cloud visualizes these locations, and this point cloud can be modified with geometry transformations to achieve desired wind effects.

A.4 Geometry Prediction

Our reverse-trained network can predict urban volumes that will produce the required wind flow and can be exported as mesh objects.

A.5 Final CFD Analysis

The predicted volumes can be used to complete a CFD prediction of the wind flow.

A.6 Discussion

Future research will focus on the inclusion of interior spaces. Passive cooling is a major factor in minimizing energy use in these spaces. The input for the reverse direction would be improved if pedestrian comfort, for instance, was used. Our current method only accounts for wind in one direction. This works in places where a dominant wind direction exists. Areas with variable wind directions would require accounting for multiple directions. The forward network is capable of predicting these multiple wind directions and can be combined.