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Flow activity-based sampling (FABaS) of 3D LES-generated flow fields for AI-based flow compression and prediction

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Summary

Flow image-based deep learning methods are emerging as a promising alternative to advance the wind-resistant design of civil structures. A key milestone for their effective and realistic implementation due to ever increasing simulation sizes is flow compression. The sampling strategy is a fundamental step in any vision-based compression technique, enabling the capture of all relevant flow features that permit the reproduction of aerodynamic phenomena, including flow-induced forces and flow characteristics in the near and far wake. While reproducing the forces can be achieved by harnessing signed distance functions (SDF), the accurate reproduction of the far field requires a more refined strategy. This investigation proposes Flow Activity-based Sampling (FABaS), a strategy that combines SDFs with flow field activity data to create a combined probability distribution that automatically selects optimal samples in both the near and far fields. The methodology is tested in a 3D LES-generated flow field around a bluff body.

Keywords: *Compression, Flow Activity, Deep Learning, Image Sampling, Flow Fields, LES*

1 INTRODUCTION

Current exascale supercomputing trends (Chang et al., 2023) are progressively bolstering the implementation of more advanced and complex deep predictive strategies. These powerful techniques have huge potential to drastically advance the wind-resistant design of civil structures. While current analysis and design techniques commonly rely on time-averaged global aeroelastic coefficients defined in the frequency domains, such as flutter derivatives or admittance functions, there is a wide range of rich information available when extracting the aforementioned parameters that can be used by harnessing deep learning approaches. A first step in this direction was taken in Cid Montoya et al. (2025), where the prediction of flutter derivatives as a function of the deck shape and reduced velocity was conducted at the force time series level taking advantage of temporal fusion transformers. Advancing this paradigm shift, flow fields contain abundant and useful information that can better guide a design process than integrates global parameters. However, the effective implementation of these approaches requires a preliminary critical step: the compression of flow data. To do so, the definition of an effective sampling strategy is a fundamental step in any vision-based compression technique to capture all the relevant flow features that permit reproducing the phenomena of interest (Yu and Wu, 2023). Mures and Cid Montoya (2025) proposed harnessing the signal distance function (SDF) concept for flow field sampling in time-varying flow domains with a high level of accuracy in the neighborhoods of the bluff body, particularly in the boundary layer region, permitting accurate extraction of the pressure and viscous forces to later obtain the resulting fluid-structure interaction parameters. However, the accuracy of SDF-guided sampling strategies decreases proportionally with the distance to the bluff body contour, making flow predictions in far fields inaccurate. To overcome this limitation, this investigation proposes a new sampling technique combining the SDF concept with a flow activity identification technique based on CFD-generated flow field information.

2 FLOW ACTIVITY-BASED SAMPLING (FABAS) AND COMPRESSION APPROACH

Compressing CFD simulation data outputs for analysis, visualization, and training of deep learning image-based flow prediction models, entails first converting flow field information to images. As such, they can be discretized for each time step t as a set of images $\psi \in \mathbb{R}^{d \times w \times h}$. We aim to reconstruct the image sets for the full simulation ψ_t, $\forall t = 1, \ldots, T$. Being T the total time step number that the simulation contains. As we only have mesh data for simulation cell centers, a strategy for optimally converting (i.e., sampling) that information to images without losing high amounts of information is essential.

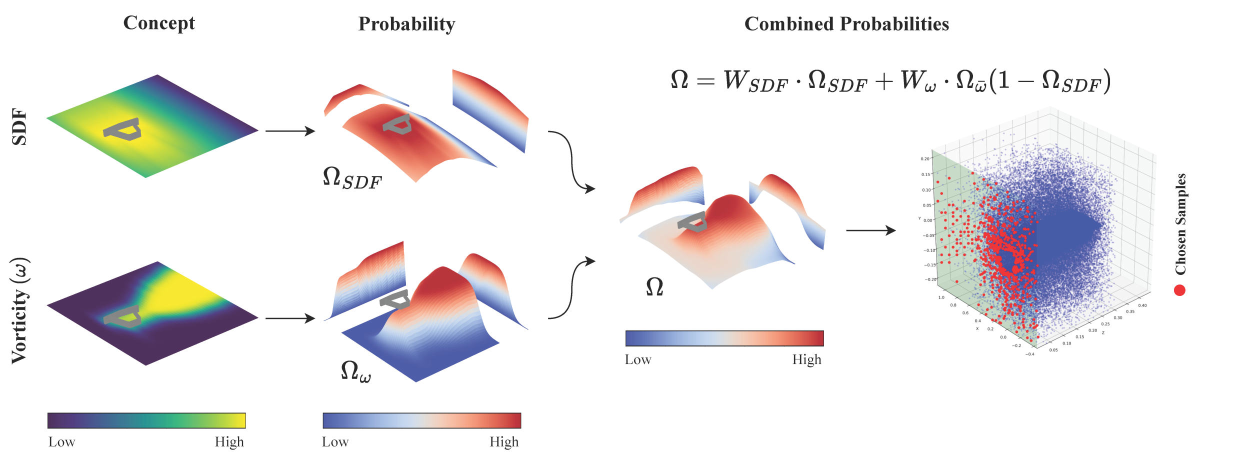

Figure 1: High-level overview of the proposed flow activity-based sampling (FABaS) methodology, which is integrated with implicit neural flow compression techniques to enhance the compression capabilities.

The proposed flow activity-based sampling (FABaS) approach synergistically combines the advantages of SDF-guided sampling with information obtained from the flow fields to effectively sample complex 3D flows (see Figure 1). This is achieved by defining a combined probability distribution along the flow domain that enables sampling storage points, or pixels, in the relevant areas of the flow domain, including the near boundary layer flows and the far wake flows, by defining the sampling probability as:

$$\Omega = W_{SDF} \cdot \Omega_{SDF} + W_\omega \cdot \Omega_{\bar{\omega}} \cdot (1 - \Omega_{SDF}), \quad (1)$$

where Ω is the combined probability, Ω_{SDF} is the probability based on the SDF of the bluff body geometry, and $\Omega_{\bar{\omega}}$ is the probability defined based on time-averaged vorticity fields. These probabilities are weighted by the terms W_{SDF} and W_ω for the SDF and vorticity fields, respectively. Finally, the term $\Omega_{\bar{\omega}}$ is multiplied by the term $(1 - \Omega_{SDF})$ to increase the weight of the flow activity in the far fields to ensure that the flow features at the far wake are properly captured.

Additionally, inspired by image-wise implicit neural representations (Tancik et al., 2020), we propose to encode fluid information as a mapping function $f_\theta : \mathbb{R} \rightarrow \mathbb{R}^{4 \times d \times h \times w}$, being θ the trainable neural network weights. Time and spatial representations are processed using a small Multi-layer Perceptron (MLP). A small transformer is used for disentangling spatial information. The final neural network weights after training contain the compressed flow field information. Images reconstructed by the neural network produce the desired output flow fields $\boldsymbol{p}$, $\boldsymbol{u}$, $\boldsymbol{v}$, and $\boldsymbol{w}$.

3 APPLICATION CASE: 3D LES OF A BLUFF BRIDGE DECK

A single-box deck similar to the Sunshine Skyway Bridge deck is used as application example in this investigation as a representative example of a bluff body. Detail on the geometrical configuration are reported in detail in Verma et al., 2024. The three-dimensional computational domain consist in a cuboid of dimension 38.5 B x 27.0 B x 1.0 B, where B is the deck width, in the x, y and the z direction respectively. The wind velocity is $U = 20$ m/s in the x direction, and the Reynolds number is $Re = 6.0 \cdot 10^5$. The simulation is solved adopting Large Eddy Simulation (LES) using the Wall Adapting Local Eddy Viscosity (WALE) model. Figure 2 (a-c) shows the 3D mesh adopted for this simulation and subplot (d) shows a slice of the flow field. Several verification and validation studies were carried out by comparing the time-averaged force coefficients with some experimental and numerical work found in the literature (Mannini et al., 2016; Verma et al., 2024).

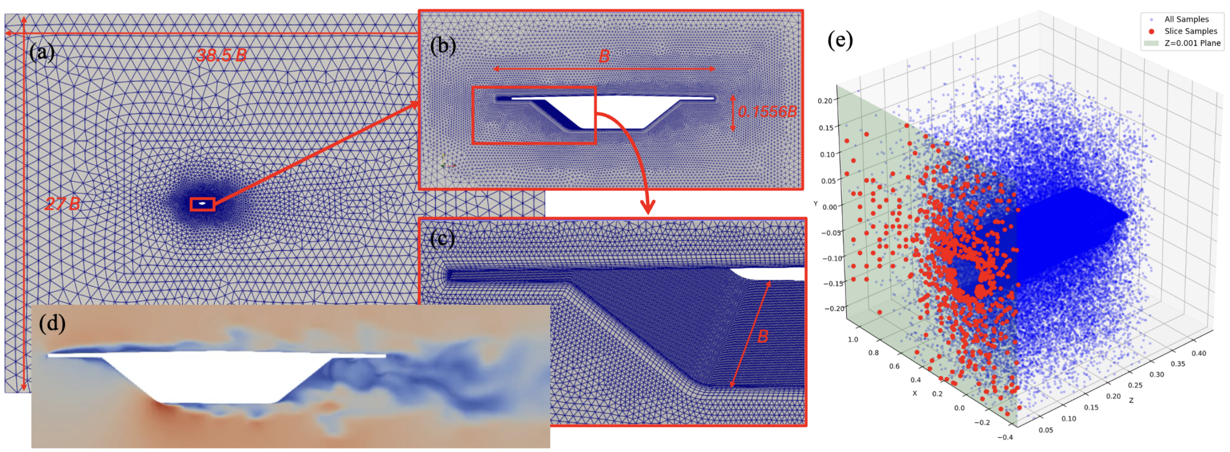

Figure 2: Overview of the mesh used in the 3D LES simulations (a-c), (d) instantaneous flow field, and (e) importance sampling generated by FABaS in the 3D flow using a resolution of 150 x 96 x 32

4 PRELIMINARY RESULTS

Figure 2 (e) shows the set of samples obtained using the proposed 3D importance sampling strategy based on the FaBAS concept described in Section 2. To facilitate its interpretation, a plane at Z=0.001 with all its samples ($150 \times 96 \times 32$) is marked in the representation, where it can be seen that the number of samples grows as we get closer to the bluff body surface, following the priorities dictated by FABaS. Such adaptive sampling is pivotal for accurately extracting relevant flow features in the neighborhood of the deck surface, an essential step for the precise estimation of wind-induced forces. Preliminary results incorporating this subsequent neural network compression layer demonstrate compression ratios reaching 2500:1, with a corresponding Mean Average Precision Error (MAPE) of $2.3\,\%$ for the reconstructed fields.

5 CONCLUDING REMARKS

This study presents FABaS, a new approach designed to overcome the limitations of geometry-based sampling in the compression of 3D flow fields. By defining a combined probability distribution that weights the Signed Distance Function (SDF) and the time-averaged vorticity field,

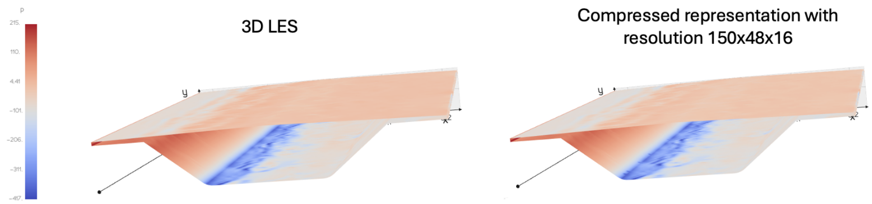

Figure 3: Instantaneous pressure (p) obtained with the CFD simulation and the flow field image volume with resolution 150 x 48 x 16, leading to a compression ratio of 468:1 without further neural network compression.

the methodology balances high-resolution sampling in the boundary layer with the retention of flow features in the wake. The approach was validated on a 3D LES simulation of a bluff bridge deck. These findings suggest that FABaS is a robust method for data-driven aerodynamic prediction frameworks. By drastically reducing storage requirements without compromising physical fidelity, this technique paves the way for the integration of large scale CFD simulation data into image-based deep learning pipelines, facilitating advanced time-domain analysis and the development of digital twins for wind-sensitive civil infrastructure.

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REFERENCES

Chang, C., Deringer, V. L., Katti, K. S., Van Speybroeck, V., Wolverton, C. M., 2023. Simulations in the era of exascale computing. Nature Reviews Materials, 8(5), 309-313. https://doi.org/10.1038/s41578-023-00540-6

Cid Montoya, M., Mishra, A., Verma, S., Mures, O. A., Rubio-Medrano, C. E., 2025. Aeroelastic force prediction via temporal fusion transformers. Computer-Aided Civil and Infrastructure Engineering, 40(15), 2098-2129. https://doi.org/10.1111/mice.13381

Mannini, C., Sbragi, G., Schewe, G., 2016. Analysis of self-excited forces for a box girder bridge deck through unsteady RANS simulations. Journal of Fluids and Structures 63, 57–76. https://doi.org/10.1016/j.jfluidstructs.2016.02.007

Mures, O. A. and Cid Montoya, M., 2025. Signed distance function biased flow importance sampling for implicit neural compression of flow fields. Computer-Aided Civil and Infrastructure Engineering, 40(17):2434-2463. https://doi.org/10.1111/mice.13526

Tancik, M., Srinivasan, P., Mildenhall, B., Fridovich-Keil, S., Raghavan, N., Singhal, U., Ramamoorthi ,N., Barron ,J., Ng, R., 2020. Fourier features let networks learn high frequency functions in low dimensional domains. Advances in neural information processing systems, 33, 7537-7547. https://dl.acm.org/doi/abs/10.5555/3495724.3496356

Verma, S., Cid Montoya, M., and Mishra, A., 2024. Shape- and frequency-dependent self-excited forces emulation for the aero-structural design of bluff deck bridges. J. Wind Eng. Ind. Aerod., 252:105769. https://doi.org/10.1016/j.jweia.2024.105769

Yu, X., Wu, T., 2023. Simulation of unsteady flow around bluff bodies using knowledge-enhanced convolutional neural network. Journal of Wind Engineering and Industrial Aerodynamics, 236, 105405. https://doi.org/10.1016/j.jweia.2023.105405