

Digitization of Wind Tunnel Experiments An AI-Based Approach to Wind Field Reconstruction and Visualization

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Summary

Urban wind turbulence poses significant risks to UAVs (Unmanned Aerial Vehicle), yet current measurement techniques like PIV and CFD struggle with cost and environmental complexity. This study introduces a computer vision framework to digitize wind tunnel experiments using multi-angle video of smoke tracers. The methodology employs a dual-stage training pipeline: first reconstructing static building geometries via implicit fields, and subsequently capturing dynamic fluid motion through physics-constrained trajectory encoding. This approach successfully recovers time-resolved 3D flow fields even from sparse and occluded inputs. By exporting the reconstructed fields as multidimensional matrices, the framework enables the quantitative extraction of critical aerodynamic features, such as velocity gradients and vortex structures. Ultimately, this work provides a low-cost, high-accuracy solution for analyzing fluid-structure interactions to support safer urban air mobility.

Keywords: *Blunt Body Aerodynamics, Computer Vision, Wind Tunnel*

1 INTRODUCTION

As urban transport networks reach capacity, the skies above cities are quickly becoming the next frontier for logistics. A vast delivery network comprising autonomous unmanned aerial vehicles (UAVs) and electric vertical takeoff and landing (eVTOL) aircraft will revolutionise the future of parcel delivery and passenger transportation (Doo et al., 2021). However, within the "artificial canyons" formed by skyscrapers, wind becomes filled with unpredictable turbulence, vortices, and downdrafts (Tominaga and Stathopoulos, 2013). These complex dynamic flow fields, generated by fluid-structure interaction, are major obstacles to safe drone flight and energy efficiency (Chodnicki et al., 2022). Existing methods face limitations: Computational Fluid Dynamics (CFD) is computationally expensive for complex environments (Blocken, 2015); physical sensors like LiDAR suffer from blind spots and high costs (Kim et al., 2023); and standard Particle Image Velocimetry (PIV) is typically restricted to 2D slices or requires prohibitive hardware for 3D tomography (Scarano, 2012). To address these gaps, this study introduces a framework that uses computer vision to digitize wind tunnel experiments. The primary objective is to utilize smoke tracers and Neural Radiance Fields (NeRF) to visualize invisible airflow, converting it into a time-resolved, three-dimensional digital model. Even when camera views are sparse or partially blocked by objects, the system integrates video data to reconstruct a complete flow field. This approach enables the full-field observation of how wind interacts with structures, effectively overcoming the limited spatial coverage of traditional experimental tools.

2 METHODOLOGY

The methodology outlines a flow field digitization process deployed in atmospheric boundary layer wind tunnels, which is divided into two key stages. First, a specialized video recording system is established to capture smoke flow around buildings. Hardware is carefully calibrated to ensure clear, synchronized footage from multiple angles, serving as the reliable foundation for reconstruction. Second, computer vision models are utilized to transform these video inputs into a

comprehensive digital flow field. Specifically, a Physics-Informed Neural Radiance Fields (NeRF) model is applied to distinguish moving smoke from the static environment. By integrating basic fluid dynamics rules directly into the learning process, the system generates a 3D digital model that accurately reflects real-world physics and velocity, going beyond simple visual imitation.

3 RESULTS

Figure 1 presents the reconstruction results for a dynamic smoke field interacting with two building models. The first two panels demonstrate a visual comparison between the camera’s raw footage and the AI-generated output. Visually, the neural network accurately renders both the rigid building structures and the fluid smoke, effectively handling the complex color relationships between the fluid and the background. Crucially, these images are rendered from a novel view—a perspective that was not seen by the deep learning model during the training phase. The model maintains high fidelity even in this unseen angle, correctly reconstructing flow patterns that envelop the buildings and pass through the narrow gaps. This proves that the network has learned the true 3D volumetric structure of the wind field, rather than simply memorizing the training videos. The third panel visualizes the structural fidelity using the Structural Similarity Index (SSIM). The predominant deep blue color indicates high fidelity, verifying that the fully reconstructed 3D digital twin matches the physical reality with high precision.

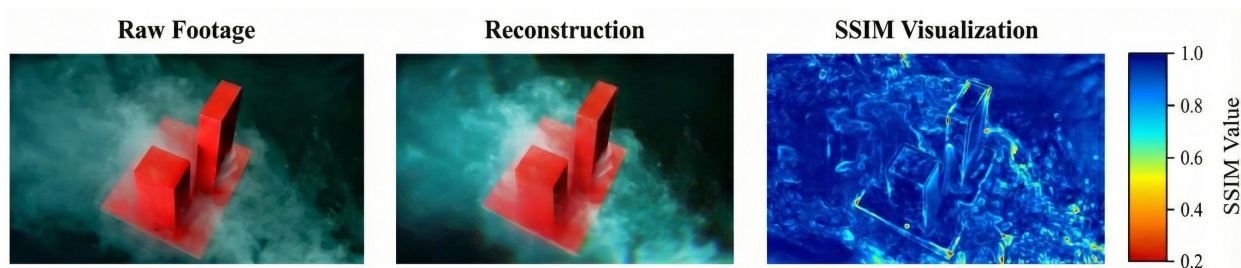


Figure 1: Visual comparison of reconstruction on two buildings with smoke interaction. Columns show (from left to right): Raw Footage, Reconstruction, and Reconstruction Fidelity. Higher SSIM values indicate better fidelity.

4 CONCLUSIONS

This study validates a real-world to digital framework for digitising fluid-structure interactions in wind tunnels, which is a significant step forward in the field. The proposed physics-based NeRF model demonstrates high fidelity in reconstructing static geometries even under occlusion, while successfully decoupling and reproducing dynamic smoke patterns with physical plausibility. Although capturing microscopic high-frequency details remains a limitation, the framework excels at reconstructing the large-scale and meso-scale flow features that dominate urban wind topologies. By effectively converting sparse video inputs into time-resolved 3D flow fields, this method provides a critical tool for analyzing complex airflows in urban canyons. Ultimately, this technology offers essential data support for safe UAV route planning, advancing the transition of logistics from ground transportation to three-dimensional aerial delivery.

5 REFERENCES

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