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A Gappy POD approach to reconstruct the wind field in urban environment for air mobility applications

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SUMMARY: (10 pt)

A novel method to estimate the wind field in an urban environment is presented. The method relies on a prior database of CFD simulations that is interpolated using a feed from a limited number of pointwise wind sensors. The CFD database is obtained by performing RANS simulations of a domain representative of downtown Los Angeles. Dedicated RANS calculations are also performed to simulate the sensor feed and provide validation test cases. The wind field estimation is obtained through the Gappy POD approach, which relies on a decomposition of the CFD database into proper orthogonal decomposition (POD) modes. The accuracy of the wind field estimation is investigated as a function of the number of sensors in the domain. Furthermore, the effect of different sensor placement strategies is considered.

Keywords: CFD, UAM, ML

1. INTRODUCTION

Urban Air Mobility is an emerging way of connecting people and goods utilizing Unmanned Aerial Vehicles (UAVs) and Vertical Take-Off and Landing aircrafts (VTOLs). Several UAV and VTOL applications are expected to take place in urban environments, especially at lower elevations, and in potentially high traffic densities. Many challenges exist when operating these vehicles in an urban environment including air-to-air, air-to-ground and air-to-infrastructure collisions, as well as issues linked to energy consumption, noise, visual pollution, limited or deteriorated navigation performance and complex urban micro-weather conditions.

As part of the weather variable, the effects of wind in intricate urban environments present complex challenges to aerial vehicle operations. Even though urban environments typically reduce the mean wind velocity within their corridors due to wind sheltering, high turbulence regions can still be experienced due to complex aerodynamic mechanisms like downwash, channelling and corner acceleration. Turbulence, which is typically associated with a rapid change of wind velocity and direction, is more impactful to the stability of UAV and VTOLs than high-velocity magnitudes. Indeed, while existing stability systems usually compensate for large uniform velocities by inducing a counterbalancing drift, the rapid change in wind direction may lead to deviations in path, increase the risk of crashes and more generally influence the vehicle operability.

To mitigate those effects, it is suitable to identify methodologies that can capture the wind complexity in an urban environment and produce reliable data for operations. This can be achieved by either increasing the sensing infrastructure (e.g., ground sensors, lidar) or by adopting numerical methodologies that are able to “fill the gap”. As part of the numerical approaches, Computational Fluid Dynamics (CFD) offer the opportunity to directly model the effect of the natural and man-built environment up to arbitrary level of complexities.

While CFD offers strong advantages in terms of flow physics and spatial resolution, it can be computationally prohibitive for an operational environment in which data are required in real-time. To solve this problem, we apply a Gappy Proper Orthogonal Decomposition (Gappy POD) approach where computationally intensive CFD is performed in advance and where local wind information is reconstructed in real-time using a limited number of wind sensors. In effect, this strategy increases the resolution by “mapping” a finite number of measurements (e.g., wind velocity or other variables) into an infinite number of evaluation points in the urban environment. As no experimental wind measurements are available at this stage, the wind information are obtained from simulated wind sensors of selected CFD test cases.

The present contribution applies the Gappy POD as a mapping strategy (Ebert, 2023a) to the CFD database generated by DM-AirTech’s software (Milani, 2021). The investigated urban area is the city of Los Angeles, which is one of the most promising cities for early UAM-adoption. Specifically, we analyse the suitability of applying the methodology under the constraints that are typical of an industrial application. The presented contribution does not rely on specific sensor installations, but provides the flexibility to install the sensors performing the assimilation within the operational environment.

2. METHODOLOGY

The methodology consists of two steps, (1) the creation of a CFD database and (2) the wind reconstruction based on sensor feed. In the present investigation, the sensor feed is simulated by dedicated CFD runs. Operational testing with real sensors is left to future endeavours.

2.1. CFD database

The CFD database is a collection of wind fields which characterizes the urban environment in terms of wind flow at the building scale resolution (<10 m). The database is generated with the objective of characterizing the wind field in downtown Los Angeles in the most “meaningful” conditions from an operational perspective, i.e. by providing wind statistics on the wind rose. Here, the CFD database has been obtained via DM-AirTech’s software, which has been set to compute the database based on the Reynolds-averaged Navier Stokes (RANS) equations, a snapshot of which is provided in Figure 1. Multiple CFD simulations were conducted for winds blowing from

every 22.5 degrees, resulting in a total of 16 CFD runs covering 360 degrees. Recent results from Ebert (2023b) have shown that increasing the angular resolution of the CFD database does not necessarily increase the accuracy of the wind field reconstruction by Gappy POD. The simulations were performed at velocities of 2.5 m/s and 5 m/s at 10 m Above Ground Level (AGL). This extensive CFD dataset forms the basis for the Gappy POD approach.
The wind field estimation by the Gappy POD will then be applied to scenarios where the wind direction and velocity is not included in the database. By using the dataset for two different reference velocities, it will be shown that the POD modes of the system are independent to non-dimensional wind fields. While the proposed RANS approach does not allow for a direct investigation of unsteady flow features at this stage, it is seen as a required compromise between scientific rigour and feasibility in an engineering framework.

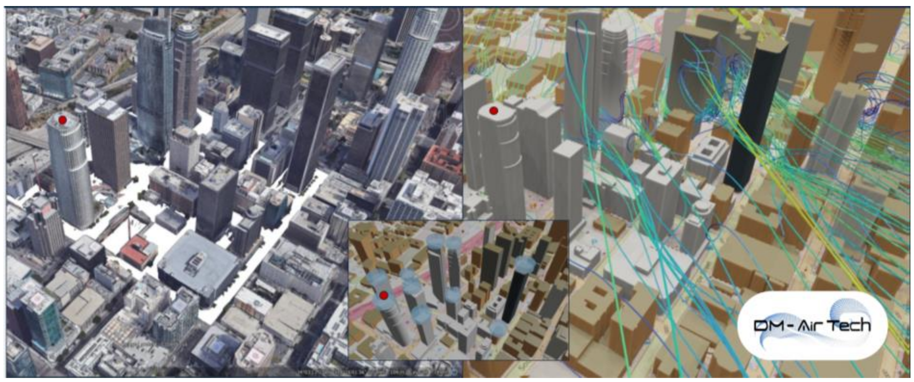

Figure 1: Snapshot of the Los Angeles downtown city center, visualized by Google Earth (left) and CFD sample.

The simulated domain is representative of the downtown area of the city of Los Angeles. It is characterized by three concentrical portions: the inner domain, the outer domain and the blended region. The inner domain directly models the buildings while the outer domain and blended region use roughness to represent the urban texture. The blended region has the purpose of transition terrain between the inner domain with its orography characteristics and the outer flat region. This way the wind enters the domain horizontally and keeps being tangent to the terrain up to the region of interest. The complete domain is a cylinder whose base is centred in (34.0495°, -118.2608°) and which has a height of 550 m. Logarithmic profile is used as input for atmospheric boundary layer.

2.2. Wind field estimation by Gappy POD

The purpose of the wind field estimation is to interpolate the CFD database with data from a limited number of sensors to obtain an approximation of the wind field on the complete domain without having to perform any new CFD simulations. This is done using the Gappy POD approach, first introduced by Everson and Sirovich (Everson, 1995).

In a first step, the CFD database representing the wind velocity fields $u(\mathrm{x}, \varphi)$ is arranged in a large snapshot matrix and decomposed into POD modes (Weiss, 2019):

$$u(\mathrm{x}, \varphi) = \sum_{k=1}^{m} a_k(\varphi)\psi_k(\mathrm{x}), \tag{1}$$

where the expansion coefficients a_k depend on the wind angle φ and the POD modes $\Psi = \left[\psi_{u_x}, \psi_{u_y}, \psi_{u_z}\right]$ are defined on the spatial domain x $\in$ (x, y, z). In practice, both modes and expansion coefficients are obtained through the singular value decomposition of the snapshot matrix S $\in R^{3n \times m}$, where n is the number of sample points and m is the number of wind directions.

In a second step, a limited number of wind sensors are chosen in the domain and the complete high-dimensional flow field is reconstructed through a linear combination of the POD modes that is compatible with the sensor values. Specifically, an incomplete wind field is represented by the sparse velocity vector $\tilde{u}$ that includes the wind velocity data from a CFD test case u_{test} that simulates the sensor feed. This test case is not included in the snapshot matrix and is solely used to simulate the sensor data. The sensor locations are covered in the measurement matrix P_{mask} (Eq. (2)). The key part of the Gappy POD is to estimate the expansion coefficients $\tilde{a}$ by solving a linear system with the POD modes and the incomplete velocity vector $\tilde{u}$. The full-state wind field reconstruction of the simulation test case $\hat{u}_{test}$ is then calculated with the POD modes ψ and the expansion coefficients $\tilde{a}$ (Eq. (3-4)). A detailed description of the applied Gappy POD approach is presented in Ebert (2023a).

$$\tilde{u} = P_{mask}\, u_{test} \tag{2}$$

$$\tilde{u} = P_{mask} \sum_{k=1}^{r} \tilde{a}_k\, \psi_k \tag{3}$$

$$\hat{u}_{test}(x, y, z) \approx \psi \tilde{a}. \tag{4}$$

The Gappy reconstruction is performed on the velocity components u_x, u_y and u_z and the velocity magnitude of the wind field is calculated by solving $\sqrt{u_x^2 + u_y^2 + u_z^2}$.

The accuracy of the wind field reconstruction by Gappy POD is strongly dependent on the spatial positioning of the wind sensors. In this work, two specific approaches will be tested. In a first approach, the sensors will be placed according to the DEIM algorithm introduced in Chaturantabut (2010), which searches for appropriate sensor locations to perform the data reconstruction. The advantage of DEIM is that the sensors are suitably placed by the algorithm to limit the reconstruction error. However, the main drawback is that the sensors might not be suited in practice because of accessibility constraints. Therefore, the second approach will be to use pre-defined sensor positions that are selected based on practical feasibility of their installation.

3. RESULTS:

In the presentation, the wind fields estimated by Gappy POD will be analysed. The accuracy of the estimation will be investigated by calculating the root-mean-square reconstruction error that defines the deviation between the reconstructed and the original wind field (here obtained by CFD). In particular, the accuracy of the wind field estimation with ideal sensor placement will be compared to the case of accessible sensors. This will allow us to draw conclusion about the limitations of the proposed approach in an actual urban environment. Furthermore, the required number of sensors will also be investigated.

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