Master's Thesis

Czech Technical University in Prague

F3

Faculty of Electrical Engineering
Department of Cybernetics

Volumetric Wind Prediction Around Obstacles from Onboard UAV Measurements

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Field of study: Cybernetics and Robotics
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MASTER‘S THESIS ASSIGNMENT

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Master’s thesis title in English:

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Master’s thesis title in Czech:

Volumetrická predikce vetru z UAV měření

Guidelines:

1. Familiarize Yourself with Computational fluid dynamics (CFD) simulations: Conduct a thorough review of existing CFD aproaches for wind simulation techniques in urban environment [1].
2. Familiarize Yourself with Neural Network volumetric wind predictors: Conduct a review of current state-of-the art approaches for volumetric wind prediction. Assess the suitability of such approaches for volumetric wind prediction from onboard UAV measurements [2],[3].
3. Develop fixed wing UAV model: Develop a fully differentiable fixed-wing UAV model that will model interaction of volumetric wind fields with UAV geometry [4].
4. Develop a Neural Network wind predictor: Based on your evaluation, design and appropriate neural network volumetric wind predictor. Create a training dataset based on CFD wind simulations and developed model. Train the neural network based on backpropagated error from difference of predicted and ground truth trajectories. Suggest a suitable loss that further constrains the predicted wind field from first principles such as Navier-Stokes equations. Take inspiration in Physics-Informed Neural Networks.
5. Predictor verification: Evaluate the predictor on test datasets and assess whether the prediction accuracy is sufficient for UAV feed forward control.

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Abstract

Flying unmanned aerial vehicles (UAV) in urban environments is challenging due to complex wind patterns caused by buildings, streets, and other obstacles. These generate turbulences, gusts, and localized vortices that can destabilize flight. Conventional wind prediction methods like Numerical Weather Prediction lack the spatial resolution needed for low-altitude flight, while high-fidelity Computational Fluid Dynamics (CFD) models are too slow for real-time use. This thesis presents a neural network that predicts time-averaged wind fields from urban geometry and mesoscale wind measurements. The approach combines supervised learning on CFD-generated data with a self-supervised refinement phase that learns from simulated UAV trajectories. A differentiable UAV dynamics model and physics-informed losses guide this refinement process. Both approaches are trained and validated using CFD simulations. The neural predictor is shown to produce accurate wind estimates in small urban environments, with output suitable for high-level UAV decision-making tasks such as path planning.

Keywords: Computational Fluid Dynamics, unmanned aerial vehicle, time-averaged wind flow, neural network wind prediction, trajectory-based learning, data-driven learning, physics-informed learning

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Abstrakt

Létání bezpilotního letounu (UAV) v městském prostředí je náročné kvůli složitým větrným jevům způsobeným budovami, ulicemi a dalšími překážkami. Tyto prvky vytvářejí turbulence, poryvy a lokalizované víry, které mohou destabilizovat let. Konvenční metody predikce větru, jako jsou numerické předpovědi počasí, postrádají prostorové rozlišení potřebné pro let v nízkých výškách, zatímco vysoce přesné modely výpočetní dynamiky tekutin (CFD) jsou příliš pomalé pro použití v reálném čase. Tato práce představuje neuronovou síť, která predikuje časově průměrovaná větrná pole na základě městské geometrie a mezoměřítkových měření větru. Přístup kombinuje učení na datech generovaných pomocí CFD s následnou fázi učení z trajektorií UAV simulovaných pomocí diferenciovatelného dynamického modelu UAV. Tento proces je veden fyzikálně založenými ztrátovými funkcemi. Oba přístupy jsou trénovány a validovány na základě CFD simulací. Neuronový prediktor prokazuje schopnost přesně odhadovat větrná pole v malých městských oblastech v reálnym čase a jeho výstup je vhodný pro úlohy vysoké úrovně v rozhodovacích procesech UAV, jako je plánování trajektorie.

Klíčová slova: výpočetní dynamika tekutin, bezpilotní letoun, časově průměrované proudění větru, predikce větru pomocí neuronových sítí, učení založené na trajektoriích, učení založené na datech, fyzikálně-informované učení

Překlad názvu: Volumetrická predikce vetru z UAV měření

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Chapter 1

Introduction

This thesis is part of Kolibriq, a collaborative research project between CTU FEE, the Czech Aerospace Research Centre, and Lockheed Martin, aimed at developing agile unmanned aerial vehicles (UAV) capable of operating at low altitudes in complex environments without GPS. The project investigates the use of neural-symbolic methods to enhance onboard planning and control, enabling safe flight near obstacles under conditions where traditional navigation systems fail. By combining physics-based models with modern machine learning approaches, Kolibriq seeks to advance autonomous UAV capabilities in cluttered, dynamic urban settings.

The operation of UAVs in close proximity to ground obstacles such as buildings or terrain features, offers both opportunities and challenges. Flying near the surface enables UAVs to follow terrain contours and access constrained areas that are unreachable by larger aircraft. However, doing so safely and efficiently requires a detailed understanding of the near-surface wind environment.

Accurate prediction of wind flow in urban settings remains a significant challenge. Wind behavior in these environments is strongly influenced by buildings, bridges, vegetation, and other obstacles, which generate turbulent wakes, channelized flows, and localized vortices [1]. Figure 1.1 illustrates the impact of these aerodynamic phenomena on a fixed-wing UAV flight.

The resulting disturbances introduce substantial uncertainty into the flight dynamics of UAVs, particularly for small-scale platforms that are highly sensitive to rapid fluctuations in airflow [2]. Wind tunnel experiments utilizing Particle Image Velocimetry (PIV) have been conducted to study airflow in urban environments. These experiments, carried out with inflow wind speeds ranging from $1\,\mathrm{m\,s^{-1}}$ to $13\,\mathrm{m\,s^{-1}}$, have shown that wind speeds within street canyons can increase from 7 % to 44 % [3]. Furthermore, turbulence intensities that exceed 40 % can appear in dense urban areas [4].

Figure 1.1: Example of possible disturbances induced on a fixed-wing UAV due to uneven wind flows encountered in an urban environment. Courtesy of [5].

These are speeds comparable to the normal cruise speed of small fixed-wing UAVs [6]. Such wind velocities can have a critical impact on flight trajectories, potentially leading to crashes. Without reliable wind flow prediction, UAVs must plan their paths conservatively, adding large safety margins to avoid gusts or turbulence. In addition, previous work has also shown that wind conditions can lead to planned path deviations [7] and increased battery consumption [8].

Access to real-time or prior wind predictions can significantly improve UAV operations. Previous studies have shown that incorporating wind information into path planning enables UAVs to avoid hazardous areas [9], reduce energy consumption [10] [12], and extend flight time in emergency scenarios [13].

However, existing wind prediction methods have notable limitations. The onboard sensors provide only local information and do not capture global flow behavior. Numerical Weather Prediction (NWP) models simulate atmospheric processes by solving a system of nonlinear partial differential equations that govern momentum, mass, energy, and moisture transport in the atmosphere. Although this approach is effective for regional weather forecasting, the kilometer-scale resolution of these models lacks the spatial granularity needed to capture fine-scale wind variations relevant for low-altitude UAV flight [14].

Computational Fluid Dynamics (CFD) methods are widely used to model wind flow in complex environments. Various flow modeling approaches are used in CFD, including Direct Numerical Simulation (DNS), Large Eddy Simulation (LES), and Reynolds-Averaged Navier-Stokes (RANS) simulation.