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Artificial Neural Networks for Individual Tracking and Characterization of Wake Vortices in LiDAR Measurements

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Introduction

Wake vortices captured by Light Detection and Ranging (LiDAR) instruments are typically characterized by their position and circulation strength. Retrieval of this information from LiDAR measurements is usually performed by conventional analytical algorithms such as the Radial Velocity (RV) method [1, 2]. Lack of automation and the thereby lack of fast-time processing motivate employment of alternative methods. In this work we propose the use of Artificial Neural Networks (ANNs) given their recent success for quantitatively characterizing aircraft wake vortices [3]. Previous studies made use of Multi-Layer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs), obtaining sufficient accuracy and reliability for wake vortex characterization but could not yet compete with traditional methods in terms of accuracy.

Goal

Herein we propose a machine-learning pipeline that uses bounding box estimations by a YOLOv4 network [4] to restrict the input to single vortices for the following regression CNN to achieve higher accuracy. Additionally, YOLOv4 allows us to detect different numbers of wake vortices in different LiDAR scans - making the proposed pipeline more flexible. We make use of the first approach of wake vortex parameter characterization with a CNN from [3] and combine this idea with new approaches to wake vortex detection using ANNs for object detection

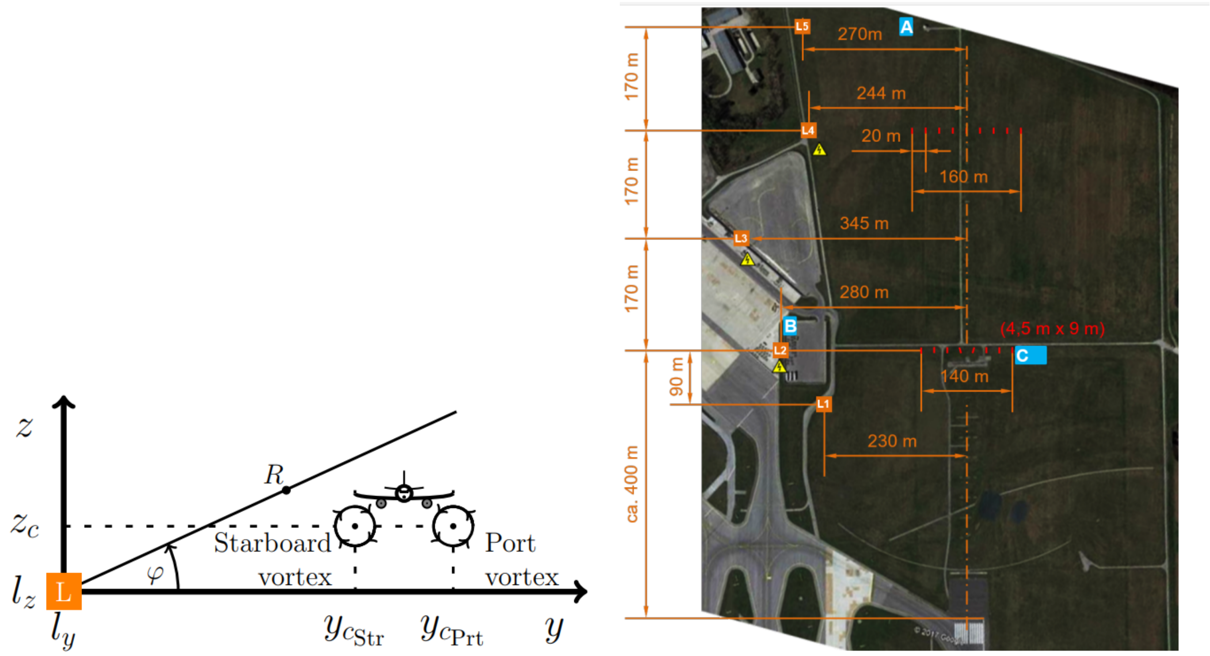
Data Set

The underlying labeled data set originates from LiDAR measurements at Vienna International Airport. A summary of the measurement campaign is given in [5]. LiDAR measurements were conducted perpendicular to the runway in RHI (range height indicator) fashion (see Fig. 1 (a)). Figure 1 (b) depicts the setup of the measurement instruments at the runway, most importantly three Leosphere Windcube 200S (1.543 μm) LiDAR were positioned at three out of five possible positions (L1-L5).

The RHI LiDAR scans are constructed from radial velocities, whereas corresponding labels were processed with the RV method - with the vortex center locations in polar coordinates $(R_t, \phi_t) \in \mathbb{R}_{\geq 0}$ and vortex circulation strength $\Gamma \in \mathbb{R}_{\geq 0}$.

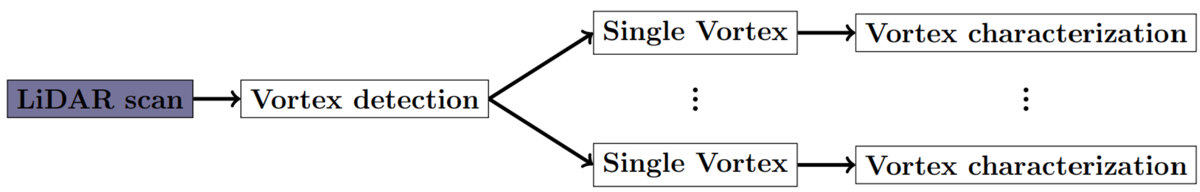
Method

A sketch of the estimation pipeline can be found in Fig. 2. The object detection and characterization accuracy are studied individually and, in the end, compared to the CNN only approach of [3]. In preprocessed form, the RHI scans are fed to the YOLO network, which delivers bounding box estimations - cut-outs - from the overall LiDAR scans entailing individual wake vortices. Subsequently, these vortex cut-outs form a vortex database, which is used to train regression CNNs, enhancing localization and circulation strength estimation further.



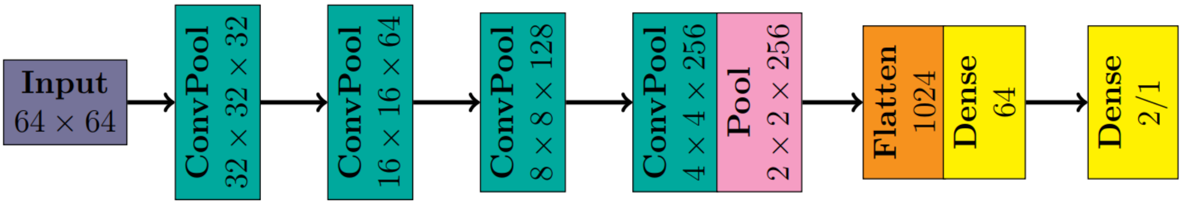
(a) (b)

Figure 1: (a) Sketch of an aircraft flying through a LiDAR measurement plane with counterrotating wake vortices. (b) Vienna measurement campaign setup of instrumentation with L1-L5 being the LiDAR positions and A-C being additional meteorological instruments.



(a)

Figure 2: Sketch of the estimation pipeline.



(a)

Figure 3: The CNN used for the regression tasks with the output dimensions of each block. The final output dimension depends on whether the vortex center or vortex circulation strength is predicted.

YOLOv4 consists of three parts: the backbone, the neck, and the head. As backbone YOLOv4 employs CSPDarknet-53. In the neck, spatial pyramid pooling (SPP) and path-aggregation network (PAN) are used. For the detection head, YOLOv3 is implemented [6]. For brevity purposes, a figure of the YOLOv4 architecture is not given here, details can be found in [4].

Following the cut-out vortices from the YOLOv4 network, we employ a regression CNN based on [3] and illustrated in Fig 3. Two separate CNNs are trained, one for localization and another for circulation strength estimation of the vortices. The CNN consists of blocks of convolutional layers followed by max pooling layers, so-called ConvPool blocks. Four of such blocks are used, with the convolutional layers having a filter size of 3×3 and the pooling layers having a filter size of 2×2 and a stride of 2. The first layer uses 32 filters which number is subsequently doubled.

Results

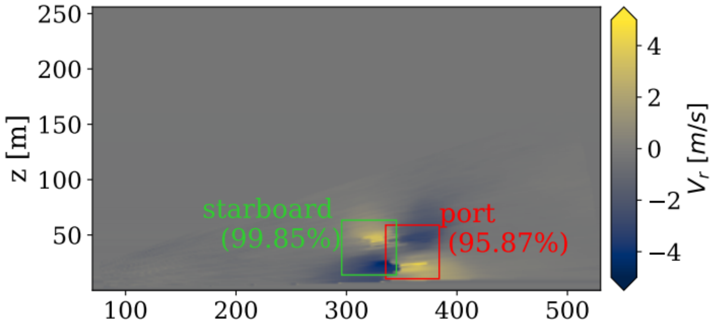
Evaluation concludes that our estimation pipeline is superior to a single CNN approach. The localization error was decreased by more than 90% and the vortex strength estimation by up to 31%, to a localization error as low as 2.87 m and a vortex strength error as low as 20.88. Furthermore, the precision of detecting hazardous wake vortices was increased by 7.51% to gain a precision of 96.11%. This pipeline can be executed while maintaining a sufficiently low computation time.

For illustrative purposes, the pipeline is showcased with a sample LiDAR scan in Fig. 4. The bounding box estimation by YOLOv4 is made, illustrated in Fig. 4 (a). Based on the bounding boxes, the vortices get cropped from the original scan (Fig. 4 (b) and (c)). Those vortices are subsequently fed into the circulation estimation CNN and the localization estimation CNN. The estimations of the CNNs can be found in Fig. 4 (d) and (e), for the starboard and port vortex, respectively. The combination of the YOLOv4 estimation and the CNN estimation is depicted in Fig. 4 (f). The average time this pipeline takes is 0.13 seconds on the HoreKa supercomputer with an NVIDIA A100-40 GPU and an Intel Xeon Platinum 8368 CPU. The CNN-only approach took 0.16 seconds for evaluation but was also performed without the usage of a GPU [3].

References

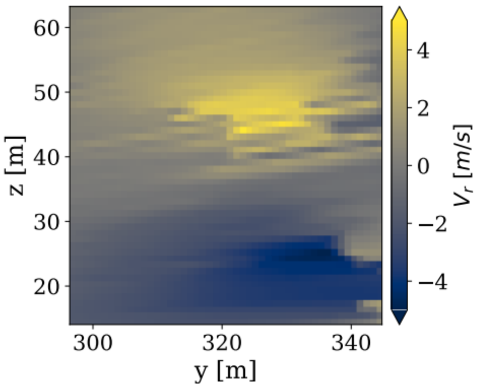
[1] Igor N Smalikho, VA Banakh, Frank Holzäpfel, and Stephan Rahm. Method of radial velocities for the estimation of aircraft wake vortex parameters from data measured by coherent doppler lidar. *Optics Express*, 23(19):A1194–A1207, 2015.

[2] Igor N Smalikho and VA Banakh. Estimation of aircraft wake vortex parameters from

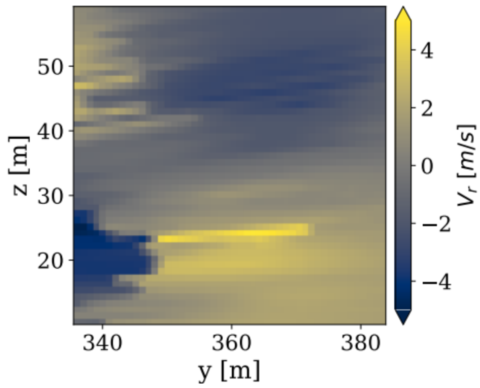


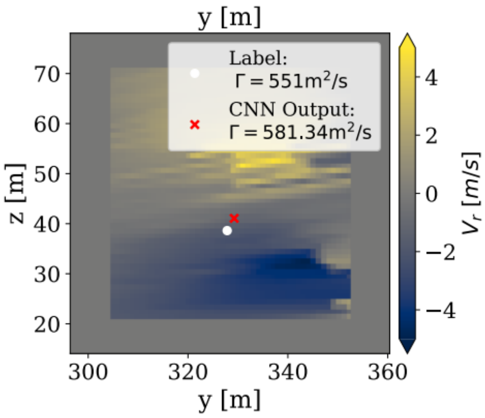
(a) YOLOv4 Predicition

(b) Cropped Starboard Vortex

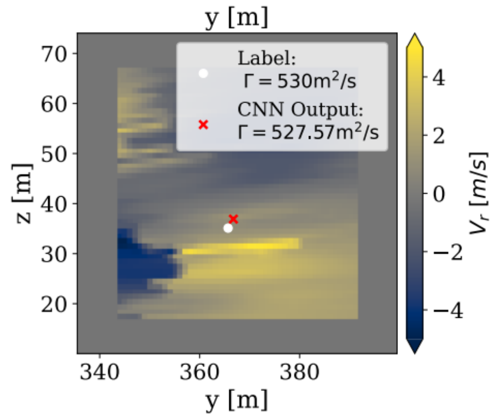


(c) Cropped Port Vortex

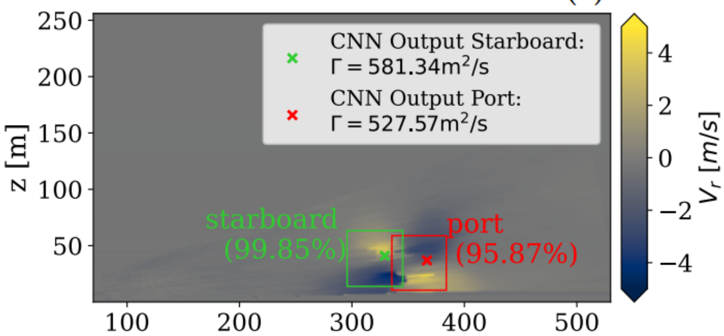




(d) CNN on Starboard Vortex



(e) CNN on Port Vortex



(f) CNN Prediction included in YOLOv4 Prediction

Figure 4: An illustration of the complete estimation pipeline excluding the initial preprocessing step.

data measured with a 1.5-μ m coherent doppler lidar. *Optics letters*, 40(14):3408–3411, 2015.

[3] Niklas Wartha, Anton Stephan, Frank Holzäpfel, and Grigory Rotshteyn. Characterizing aircraft wake vortex position and strength using lidar measurements processed with artificial neural networks. *Opt. Express*, 30(8):13197–13225, Apr 2022.

[4] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934*, 2020.

[5] Frank Holzäpfel, Anton Stephan, Grigory Rotshteyn, Stephan Körner, Norman Wildmann, Lothar Oswald, Thomas Gerz, Günther Borek, Alexander Floh, Christian Kern, Markus Kerschbaum, Roman Nossal, Johannes Schwarzenbacher, Martin Strobel, Lukas Strauss, Clemens Weiß, Sebastian Kauczok, Christian Schiefer, Harald Czekala, Gerrit Maschwitz, and Igor Smalikho. Mitigating wake turbulence risk during final approach via plate lines. *AIAA Journal*, 59(11):4626–4641, 2021.

[6] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*, 2018.