Journal of Open Aviation Science (2023), Vol.**1**
doi:10.59490/joas.2023.7215

JOAS

POSTER | ***The 11th OpenSky Symposium***

Aircraft Detection and State Estimation in Satellite Images

Peder Heiselberg[*,1] and Kristian A. Sørensen[2]

[1]Department for Geodesy and Earth Observation, National Space Institute, Technical University of Denmark, Kongens Lyngby, Denmark.
[2]Center for Security, National Space Institute of Denmark, Technical University of Denmark, Kongens Lyngby, Denmark.
*Corresponding author: ph@space.dtu.dk

(This poster paper is not peer reviewed.)

Abstract
Unidentified flying objects are aircraft that do not continuously broadcast ADS-B. They pose a risk to air traffic safety. In this study, we introduce a method for detecting and estimating the state of aircraft in Sentinel-2 multispectral satellite images. We construct a dataset of 579 ADS-B annotated aircraft from 69 Sentinel-2 images. A CNN is trained on the dataset to aircraft state vector i.e. position, velocity, heading, and altitude. This work allows real-time monitoring of flying objects in satellite images.

Keywords: Aircraft, deep learning, object detection, state estimation, multispectral image, satellite image

Abbreviations: ADS-B: Automatic Dependent Surveillance-Broadcast, AIS: Automatic Identification System, UFO: Unidentified Flying Object, UFLO: Unidentified Floating Object, CNN: Convolutional Neural Network,

1. Introduction

The use of satellites has enabled effective monitoring of large areas from space. Aircraft identify themselves with the Automatic Dependent Surveillance-Broadcast (ADS-B). It continuously transmits the aircraft state, e.g. identity, position, velocity, heading, altitude which allows air traffic monitoring. However, the ADS-B transponder can be turned off either by accident or deliberately. Unidentified Flying Objects (UFOs) pose a security risk. They may engage in illicit activities such as spying and smuggling. Satellite images enable the detection of aircraft even when the ADS-B transmission stops.

The maritime domain experiences a similar scenario. Ships carry an Automatic Identification System (AIS) transponder. Failure of continuous transmission renders the ship an Unidentified Floating Object (UFLO). Effective monitoring requires detection of the object in a satellite image and correlation to a transponder signal [1]. This established the object's identity or lack thereof. Estimating the state (velocity and heading) of the object allows its future whereabouts to be predicted.

Clouds often obscure the view of ships [2]. The maritime domain is therefore predominantly monitored by Synthetic Aperture Radar (SAR) satellites. This type of sensor can penetrate clouds and operate day and night. Yet, moving objects are Doppler-shifted by the SAR proportional to their velocity. The shift enables velocity and heading determination [3] which can be fed into predictive algorithms [4]. However, aircraft velocities are so great, that the SAR is not capable of effectively imaging them.

Aircraft often fly above the cloud cover. Detection of aircraft using optical satellites is therefore not as limited as for ships [5]. Aircraft detection has predominantly been focused on stationary aircraft [6]. But recently, flying aircraft has also seen attention [7, 5]. Only a few methodologies exist to estimate the velocity, heading, and altitude [8]. In this article, we present a methodology for simultaneous aircraft detection and state estimation.

2. Method

The methodology is divided into two sections. First, the steps of acquiring a dataset of flying aircraft are described. Second, the details on training a CNN for aircraft detection and state estimation are provided.

2.1 Data acquisition and processing

Sentinel-2 L1C satellite images were acquired over Copenhagen and South East England over the English Channel. ADS-B was collected from the OpenSky database [9] in a Fifteen-minute interval of the Sentinel-2 images sensing time. The ADS-B track was overlaid on the Sentinel-2 image and interpolated to the image sensing time. Subsequently, the aircraft in the image were annotated. As a result, n aircraft and m ADS-B positions were acquired for a given image. The ADS-B were then assigned to the aircraft in two steps. First, a regionalization algorithm with a threshold of $4km$ was applied. This created groups where the maximum distance between any aircraft or ADS-B were $4km$. Second, the Hungarian algorithm [10] was used to assign the aircraft to the ADS-B signals. A total of 69 images were processed, yielding 574 ADS-B annotated aircraft (an example is provided in Fig. 1).

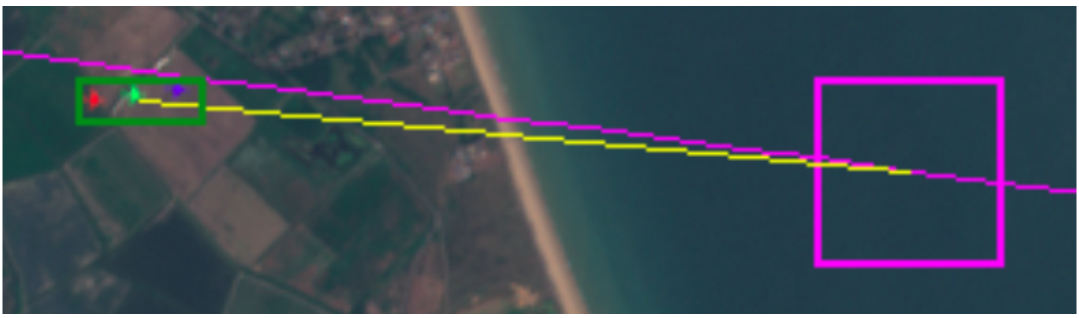

Figure 1. Sentinel-2 true color image of the southeast part of England. The magenta box indicates the interpolated ADS-B signals (magenta line) to the image sensing time. The aircraft annotation is indicated by the green box. The yellow line indicates the association of the ADS-B signals to the aircraft. See the text for an explanation of aircraft color displacement.

2.2 Detection and state estimation

A CNN is trained to detect aircraft and their state by estimating a bounding box, the velocity, heading and altitude. The aircraft state vector $S = (x, y, w, h, \theta, v, a)$ describes this information. Estimating the state vector is learned by the CNN via regression. We adopt the parameterization following [11].

$$t_x = (x - x_a)/w_a \quad t_y = (y - y_a)/h_a \quad t_w = log(w/w_a) \quad t_h = log(h/h_a) \quad t_v = log(v) \quad t_a = log(a) \tag{1}$$

$$t_x^* = (x^* - x_a)/w_a \quad t_y^* = (y^* - y_a)/h_a \quad t_w^* = log(w^*/w_a) \quad t_h^* = log(h^*/h_a) \quad t_v^* = log(v^*) \quad t_a^* = log(a^*) \tag{2}$$

where x, y, w, and h denote the center, width and height of the box. x, x_a, and x^* are the predicted box, anchor box, and ground truth box respectively (likewise for y, w, h). We included the velocity v and altitude a in the parameterization. In Fig 1 the RGB channels of the aircraft area are displaced in two directions, roughly vertical and horizontal. In this case, the horizontal is caused by the aircraft moving in the time between acquisition of the red, green, and blue images. The vertical displacement is caused by the satellite moving between the acquisition of the red, green, and blue images. From the satellite's point of view, the aircraft shadows different areas, resulting in a parallax effect. As a consequence, both the altitude, velocity, and heading are encoded in the image and can thus be extracted by the CNN. See [8] for analytical relations determining velocity and altitude.

The CNN was optimized over the smooth-L1 loss of $z = t - t^*$, where $t_\theta - t^*_\theta = atan2(\sin(\theta - \theta^*), \cos(\theta - \theta^*))$.

$$smooth_{L1}(z) = \begin{cases} 0.5z^2, & |z|<1 \\ |z| - 0.5, & \text{otherwise} \end{cases} \tag{3}$$

For the classification, we used the focal loss [12]. The dataset was split 80/20 train/test, and AdamW optimizer [13] with default settings.

3. Discussion and conclusion

In this study, we introduced a methodology for aircraft detection and state estimation using satellite imagery and ADS-B data. The approach uses CNN to estimate the aircraft state vector i.e. position, velocity, heading, and altitude. In Fig. 2 two detected aircraft and their state is shown. This work lays the foundation for real-time monitoring and tracking of flying objects, including UFOs, in satellite images.

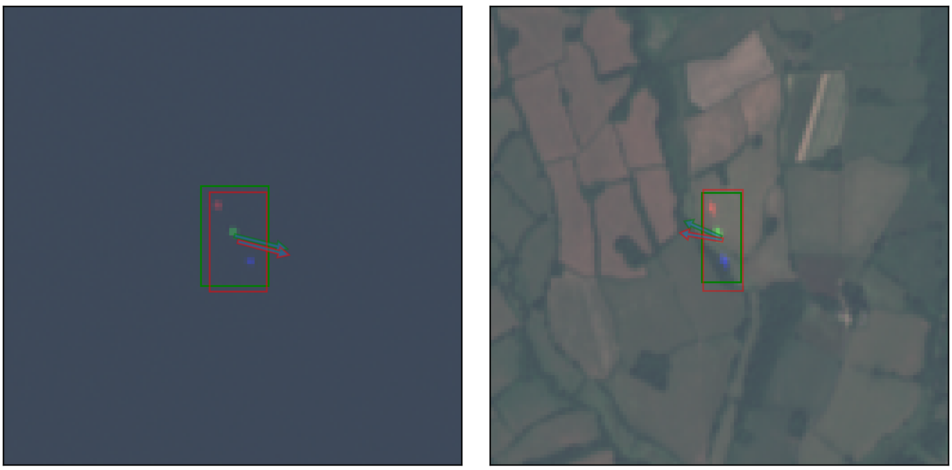

Figure 2. Detected aircraft (red box) and ground truth (green box). Arrows point in the heading direction, with size proportional to the aircraft velocity.

Acknowledgement

The authors would like to thank The OpenSky Network for providing access to the ADS-B data.

Author contributions

- Peder Heiselberg: Conceptualization, Data Curation, Methodology, Software, Writing–Original draft
- Kristian A. Sørensen: Data Curation, Software, Methodology

Funding statement

This research has not received any outside funding.

Open data statement

All data used for this study is freely available. The ADS-B data was collected from the OpenSky database [9]. Sentinel-2 images are made freely available at https://scihub.copernicus.eu/.

Reproducibility statement

The list of the 69 Sentinel-2 scene IDs are available upon request to the corresponding author. The ADS-B data and Sentinel-2 scenes can be acquired according to the open data statement.

References

[1] Peder Heiselberg, Kristian A Sørensen, Henning Heiselberg, and Ole B Andersen. "SAR Ship–Iceberg Discrimination in Arctic Conditions Using Deep Learning". In: *Remote Sensing* 14.9 (2022), p. 2236.

[2] Peder Heiselberg and Henning Heiselberg. "Ship-Iceberg discrimination in Sentinel-2 multispectral imagery by supervised classification". In: *Remote Sensing* 9.11 (2017), p. 1156.

[3] Peder Heiselberg, Kristian Sørensen, and Henning Heiselberg. "Ship velocity estimation in SAR images using multitask deep learning". In: *Remote Sensing of Environment* 288 (2023), p. 113492.

[4] Kristian Aalling Sørensen, Peder Heiselberg, and Henning Heiselberg. "Probabilistic maritime trajectory prediction in complex scenarios using deep learning". In: *Sensors* 22.5 (2022), p. 2058.

[5] Peder Heiselberg and Henning Heiselberg. "Aircraft detection above clouds by sentinel-2 MSI parallax". In: *Remote Sensing* 13.15 (2021), p. 3016.

[6] Fan Zhang, Bo Du, Liangpei Zhang, and Miaozhong Xu. "Weakly supervised learning based on coupled convolutional neural networks for aircraft detection". In: *IEEE Transactions on Geoscience and Remote Sensing* 54.9 (2016), pp. 5553–5563.

[7] Fen Zhao, Lang Xia, Arve Kylling, Hua Shang, and Peng Yang. "Mapping global flying aircraft activities using Landsat 8 and cloud computing". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 184 (2022), pp. 19–30.

[8] Henning Heiselberg. "Aircraft and ship velocity determination in Sentinel-2 multispectral images". In: *Sensors* 19.13 (2019), p. 2873.

[9] Matthias Schäfer, Martin Strohmeier, Vincent Lenders, Ivan Martinovic, and Matthias Wilhelm. "Bringing up OpenSky: A large-scale ADS-B sensor network for research". In: *IPSN-14 Proceedings of the 13th International Symposium on Information Processing in Sensor Networks*. IEEE. 2014, pp. 83–94.

[10] Harold W Kuhn. "The Hungarian method for the assignment problem". In: *Naval research logistics quarterly* 2.1-2 (1955), pp. 83–97.

[11] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. June 2014.

[12] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. "Focal loss for dense object detection". In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2980–2988.

[13] Ilya Loshchilov and Frank Hutter. "Decoupled weight decay regularization". In: *arXiv preprint arXiv:1711.05101* (2017).