ScrubberWatch

github.com/MaximilianFranz/scrubberWatch

Sandro Braun * sandro@hackundsoehne.de

Maximillian Franz * max@hackundsoehne.de

Leander Kurscheidt * leander@hackundsoehne.de

Carsten Bullemer † bullemer@searoutes.com

Winner of EIT Digital DeepHack, Hamburg, 22. - 24. November 2019

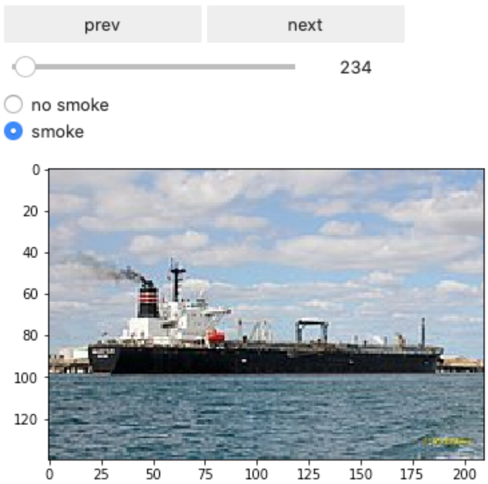

Figure 1: Annotation tool for computer vision pipeline.

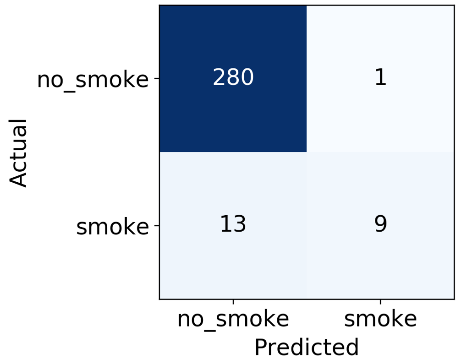

Figure 2: Confusion matrix of recognition model.

1 Introduction

With the IMO2020 resolution taking effect 1. Januar 2020, the importance of emission monitoring for vessels is bigger than ever. Previously, with the limited Emission Control Areas (ECAs) in place, it was a viable solution for operators to switch to Marine Gas Oil (MGO) or liquified natural gas (LNG) within these zones and burn the cheaper Heavy Fuel Oil (HFO) on open seas.

Starting 2020, however, every ship using HFO is required to have an Emission Gas Cleaning System (ECGS) in place, no matter where on the worlds seas. Thus, the incentive to install these so called scrubbers is now higher than ever. The pending problem is, that for operators and port authorities it is not easy to verify if scrubbers are in use without direct sensory contact with the emitted fumes.

2 ScrubberWatch

The claim of the *ScrubberWatch* project is, that the effect of the scrubber on the emitted gases can be measured through a vision based system. The underlying assumption is that the concentration of sulfur dioxide can be measured directly or indirectly via the temperature, smoke density or smoke color.

As a simple first step toward simple pollution monitoring, we built a recognition model to detect smoke on images of ships. We further built a proof-of-concept user interface to illustrate a potential use-case of the vision-based system.

2.1 Computer Vision pipeline

Dataset To detect smoke on images of ships, we built a simple recognition model. However, smoke detection and quantification is a very niche topic, which is why there is no dataset readily available. This is a problem, because state-of-the-art computer vision relies on large-scale datasets with annotated data. To solve this problem, we created an annotation tool and manually annotated a publicly available dataset of ships. We annotated if smoke emission is clearly visible or not, or more precisely 'no smoke' vs 'smoke'. The dataset we use is from the *game-of-deep-learning-ship-datasets* kaggle challenge. [Jain and Vidhya, 2019]. This dataset comprises 6000 images of ships with their type annotations in 5 categories : Cargo, Military, Carrier, Cruise, Tankers. We built a simple annotation tool that suits our problem. The annotation tool is shown in Figure 1. Using our annotation tool, we annotated 2000 images from the dataset and annotated if the smoke output is noticeable or not. We additionally scraped images of ships with significant smoke output and added it to the dataset. The overall dataset consists of 1907 images with annotation 'no smoke' and 119 images with annotation 'smoke'. We apply a 15% train-/validation split.

Recognition Model We train a simple object recognition model based on our manually annotated data. To do so, we use the winning kernel [Pattanayak, 2019] from the same kaggle challenge as the dataset and adapt it to our manually annotated data. The confusion matrix of the recognition model is shown in Figure 2. Due to the strong imbalance between classes, the model struggles to correctly classify examples of the strongly undersampled class 'smoke'. This problem could be addressed by the following measures: 1. Adding more data and rebalancing the dataset. This introduces more cost of collecting data and annotating data. 2. Optimizing the model with respect to F_1 score instead of accuracy.

2.2 Dashboard

For ScrubberWatch to be effective, the project does not only need to detect the emitted gases, but also implement information fusion with other data-sources. The feasibility was

*Hacker
†Advisor

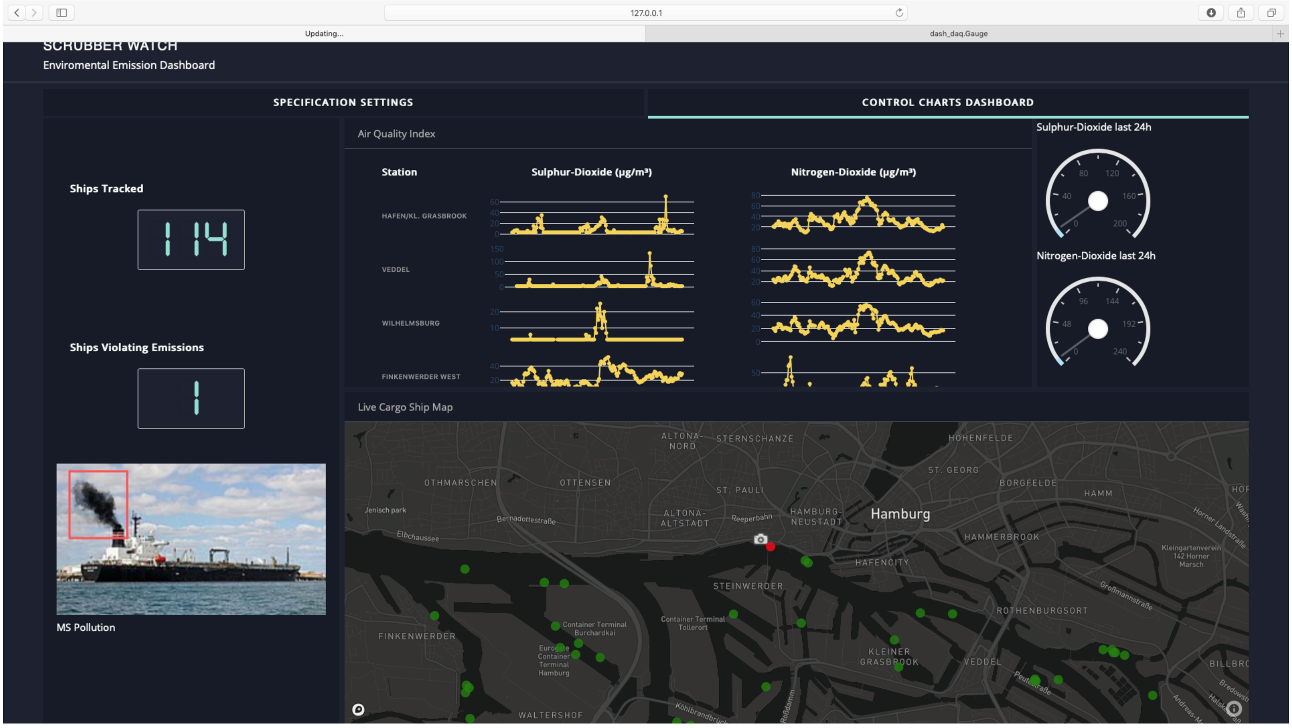

Figure 3: A Screenshot of our dashboard.

explored by working on a proof-of-concept for the dashboard. Since the position of the sensor-system is known, the offending ship can be matched with a register of ship-positions. We can therefore retrieve the IMO-number and provide the relevant meta-data of the ship to the user. To communicate the data, we designed and implemented a web-based dashboard. The dashboard is shown in Figure 3. The dashboard uses real data, except for our offending ship, the *MS Pollution*, and a fictional camera-position, which we added for demonstration-purposes. By implementing the dashboard, we sketched the usage of ScrubberWatch and positively investigated the integration with other data-sources.

3 Outlook

The ScrubberWatch project is only meant as a proof of concept towards a new approach to pollution monitoring. Further steps are required to validate our hypothesis outlined in (2). Especially, systematic research is required to ascertain the feasibility of vision estimation of sulfur dioxide concentration. For example, infrared cameras could be used to estimate the temperature of gas emissions and thus sulfur dioxide concentration. Furthermore, a sustainable business model for port authorities has to be developed. Beside this technical and economical aspects, we believe that this project points out an important direction for further development. Our belief has been consolidated by being selected as the winner of EIT Digital DeepHack Hackathon Hamburg 2019.

References

[Jain and Vidhya, 2019] Jain, A. and Vidhya, A. (2019). Game of Deep Learning: Ship datasets, Version 1. `https://kaggle.com/arpitjain007/game-of-deep-learning-ship-datasets`. This Dataset is taken from Deep Learning Hackathon organised by Analytics Vidhya.

[Pattanayak, 2019] Pattanayak, S. (2019). Ship Classification - Top 3.5 % Kernel. `https://kaggle.com/sandeeppat/ship-classification-top-3-5-kernel`.