Usability of Medium Resolution Optical Remote Sensing Images for Anomaly Detection in Maritime Surveillance Applications

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***Abstract*—As part of the project "Intelligent Assistance and Analysis Systems for Early Detection and Management of Maritime Hazardous Situations" (IntelliMar) an anomaly detection application was developed and validated based on the analysis of Automatic Identification System (AIS) and Earth Observation (EO) remote sensing data. For this task optical Earth observation medium resolution satellite data from Landsat-8 and Sentinel-2 were used and their suitability in the context of object detection was evaluated. In a two-step approach, deep-learning methods were used for object detection and classification, and the derived results were then applied to a set of anomaly rules for anomaly report generation and transmission.**

***Keywords*—remote sensing, anomaly, object detection**

I. Introduction

The overall goal of the IntelliMar project was to explore and benchmark new concepts for advanced maritime services in terms of data analysis. The consortium of industry partners AIRBUS DS and HuMaTects as well as the DLR research institutions German Remote Sensing Data Center, Institute for Communication and Navigation and OFFIS Institute therefore joined forces to significantly improve intelligent data analysis, information distribution and visualization in the field of anomaly detection by developing and validating new methods and technologies. A particular focus of the joint research work was to improve integration of different data sources and services in a maritime interconnected system as well as to develop innovative intelligent assistance and analysis services for early detection and management of maritime security scenarios. While other partners were working on anomaly detection based on Automatic Identification System (AIS) data, we tried to investigate whether this task can be complemented or fully accomplished with medium resolution satellite images. In general, remote sensing data from a variety of sensors have been used for maritime situational awareness for many years, also the number of satellites used for environmental monitoring and vessel traffic monitoring is increasing year by year. For our study, we used satellite imagery collected by the USGS Landsat-8 (L8) and Copernicus Sentinel-2 (S2) platforms that able to cover relatively large areas with image swath of 185 km and 290 km correspondingly. In this paper we present our automated framework for maritime anomaly detection and report generation. Main modules of this framework are object and anomaly detectors. Another essential component is training dataset that was used to train object detector. In the subsequent chapter these components will be described.

II. Methods and Material

2.1 Training Data

The first major operation in terms of sea traffic anomaly detection from EO data is object detection. The training dataset were generated from images acquired by the L8 and S2 platforms. Both platforms are equipped with multispectral sensors. However, for this study, only visual (RGB) bands enhanced with pan-chromatic band (operation known as pan-sharpening) were utilized to obtain images with the highest spatial resolution per pixel: 15 m for L8 and 10 m for S2.

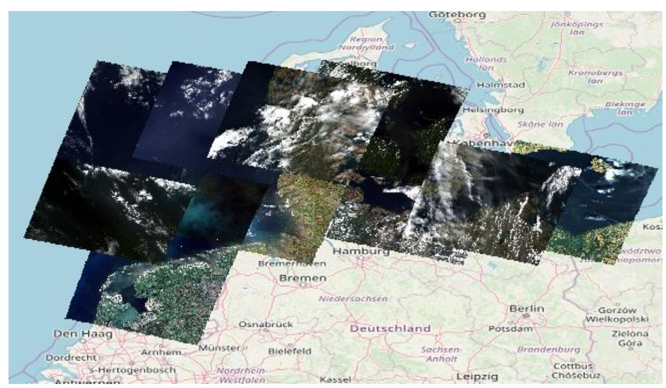

Fig.1 Area coverage for the generation of the training data.

Fig. 1 shows an example of the coverage of the satellite images of the landsat-8 mission for the area of the North Sea and the Baltic Sea, in which most of the training data was generated.

In total 82 satellite images were processed to generate training samples for the following 11 predefined object/feature classes: Oil tankers, cargo ships, container carriers, service/tug boats, passenger ships, small passenger boats, fishing boats, fish farms, offshore platforms, and windmills. The distribution of the training data among the individual classes is shown in Fig. 2.

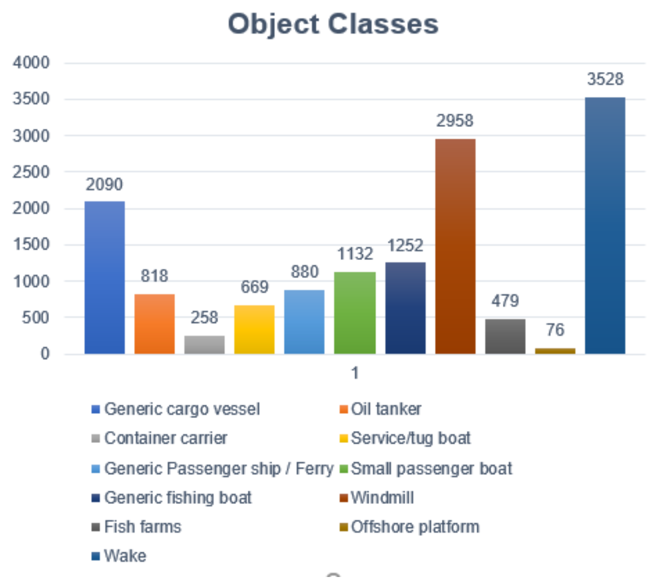

Fig. 2 Training data, distribution of object classes

The annotation of objects was performed in a semi-automatic way. After processing the satellite image, the AIS data matching the temporal and geographical coverage were retrieved. Subsequently, the AIS position reports were interpolated to get the exact locations at the time the satellite image was taken. The resulting annotations are then visually inspected and, if necessary, manually corrected or adjusted with respect to the vessel position on the satellite image. All non-vessel object classes are completely manually annotated. One training sample is a 300x300 pixel image crop containing one or more annotations. Derived training dataset is then used to train deep learning-based object detector.

2.2. *Object Detection*

Object detection, developed within this project is based on preliminary work of object recognition using very high resolution satellite data [1]. Before detection, land areas are excluded using water polygons extracted from the OpenStreetMap project [2]. Due to the relatively low image resolution of 10 or 15 meters, an additional buffer of 50 meters were applied to the land mask in order to limit object search to water areas only. The remaining water areas are sliced into small image chips of size 300x300 pixels that are further used for object detection. The object detection task is carried by a convolutional neural network (CNN). The two-stage object detector Faster R-CNN [3] with backbone network ResNet50 [4] was chosen for this task. The output of Faster R-CNN are non-oriented bounding boxes of the objects. To extract rough objects orientations and their dimensions an additional post-processing step involving classical computer vision methods as well principle component analysis (PCA) is applied. The results obtained are shown in the Fig.3. The graph contains the distribution of the “Detection Score” with respect of the trained vessel classes.

2.3. *Anomaly detection and reporting*

The information obtained after object detection is used to recognize anomalies in the given scenarios: "Appearance of vessel atypical for the area" and "Small fast boat sailing at high speed in the open sea". In both cases, the boundary condition is set that the objects (vessels) do not identify themselves via AIS. In this respect, the detection of the anomaly was done in two steps. In the first step, detected objects in the study area are automatically fused with AIS reports. In case of "Small fast boats" only small detected ships are merged with detected wakes, this is the indicator for small and fast and no AIS.

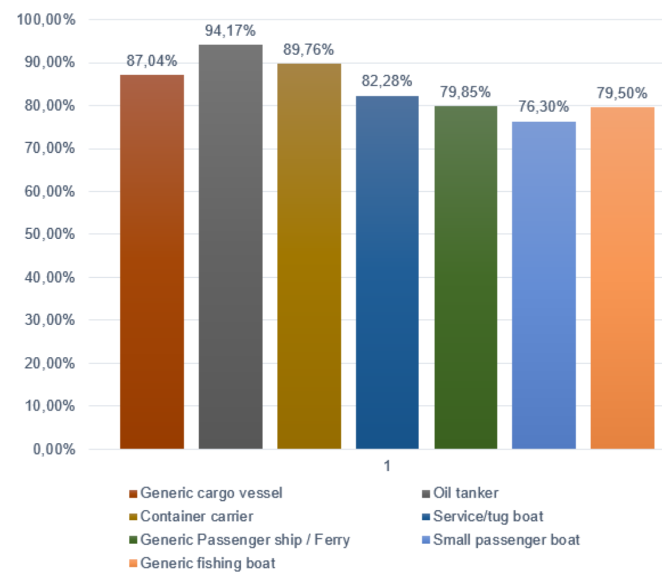

Fig. 3 Vessel Detection Score.

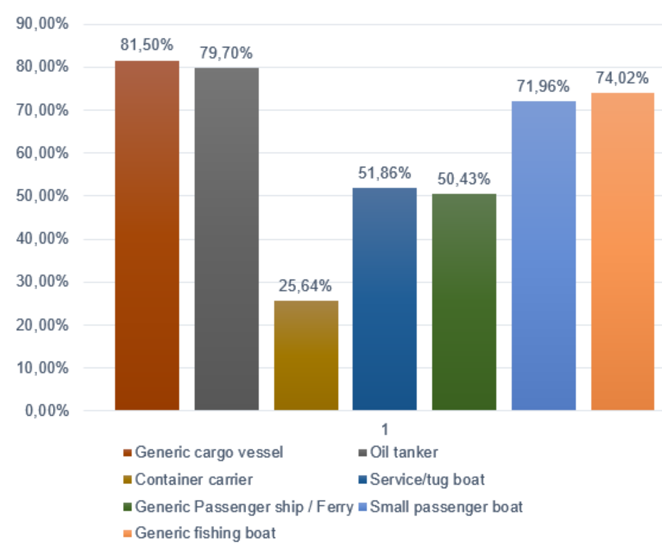

Fig. 4 Vessel Classification Accuracy.

"Appearance of vessel atypical for the area" is determined by spatial intersection of predefined vessel type against predefined polygon. Subsequently, AIS-free detections are evaluated for both rules independently. In case the anomaly was detected, a corresponding anomaly report was generated and disseminated. Fig. 4 shows the clip image result of the validation " Appearance of vessel atypical for the area ".

The Data Service Grid (DSG) developed by AIRBUS was used for report transmission. This consisted of a series of agents, the so-called DSG nodes, which were deployed at each partner location and communicated with each other via defined interfaces. In that way the report was directly ingested into the service API and displayed to the operator based on applied predefined model functions like anomaly type and criticality.

III. RESULTS

Validation of the object detection method was accomplished using 14 Landsat-8 and Sentinel-2 images. These images had not been previously included in the training process and did not contribute to model training. To evaluate accuracy, all objects in these test images were manually labeled using additional data sources such as AIS reports, as well as information provided from OpenSeaMap, e.g., windmills, to compare with the results of the automatically detected objects. While the average recognition rate of the developed processor for all classes was 79%, the classification accuracy was about 82%.

The validation of the anomaly detection was based on the scenarios already mentioned in the previous chapter. In both scenarios it was assumed that the vessels do not identify themselves via AIS. For the first scenario "Appearance of a ship atypical for the area", a study area was first simulated, in which the ships were recognized with the developed AI and fused with AIS. Finally, as a result, the ships that did not cooperatively identify themselves via AIS were reported via the DSG.

The scenario "Small fast boat sailing at high speed in the open sea" was simulated using the research vessel "JOSEPHIE" of the Office Institute. For this purpose, at the time of the satellite overpass, the boat followed a previously defined course at high speed in order to generate a wake. The AI-based object detector has successfully detected "JOSEPHINE" as "small passenger boat" together with its wake. This information triggered recognition of the "Small fast boat sailing at high speed in the open sea.

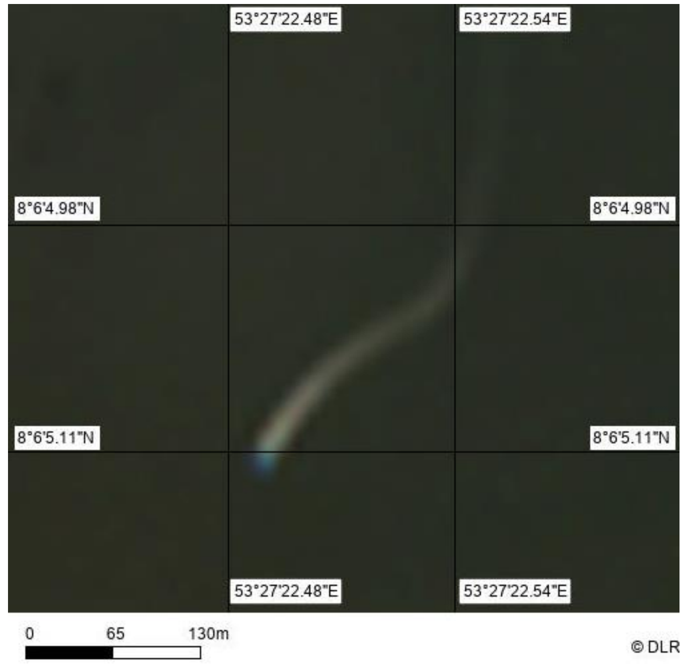

Fig. 6 Clip image of wake detection result

As a result of the validation, the usability of remote sensing data for the selected scenarios can be confirmed in principle. Especially considering relatively high object detection and classification scores. However, the quantification as well as a qualitative evaluation regarding the reliability of the anomaly detection method cannot be performed within the scope of this study due to the limited test and real data.

IV. CONCLUSION

This paper presents a method for multiclass object detection from medium resolution satellite optical images followed by anomaly detection to contribute in maritime surveillance applications. The solution includes a set of methods established in the computer vision for object detection and image processing tasks, rule-based anomaly recognition and a framework approach adapted from [5] for process automation. The results generated by the framework show that the applied method is suitable for detecting sea traffic anomalies. For the selected scenarios, the usability of medium-resolution optical remote sensing data as an independent sensor was well demonstrated. Nevertheless, there are also limitations of the application, especially under bad weather conditions. A reasonable performance in terms of processing speed (about 1-2 minutes per image) and accuracy was achieved. In the future research more, complex scenarios for anomalies can be considered. This may include e.g. behavior or trajectory analysis of AIS reports complemented by EO-based vessel detection. Furthermore, the developed framework will be integrated into the chain of near real-time processing, established for Landsat processing at the ground station Neustrelitz.

V. ACKNOWLEDGMENT

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VI. References

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