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Research Article

EURMARS: Use of Satellite Imagery as an Asset for Maritime Environment Rapid Tracking and Object Detection in Large Areas

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ABSTRACT:

The increasing complexity of maritime risks and threats requires accurate and timely identification, both for environmental and human safety. Satellite observations enable comprehensive surveillance of large maritime areas which is essential for detecting and responding to environmental changes and potential threats. The Horizon Europe project EURMARS, aims to develop and validate a multi-purpose observation platform to enhance detection capabilities for various risks and threats. This paper proposes a novel Earth Observation (EO) data processor, designed to handle various open-access satellite images from Sentinel-1, and Sentinel-2 as well as video from the NEMO-HD microsatellite. By employing Object-Based Image Analysis (OBIA) through machine learning and deep learning techniques, the detection of vessels is achieved using synthetic aperture radar (SAR), multispectral images, and RGB video. Data from positioning systems is utilized to ensure comprehensive monitoring and to validate the results of the method. The integration of satellite imagery with AIS data is a key element of the vessel detection methodology, enhancing the accuracy and reliability of maritime surveillance. By projecting AIS data onto satellite imagery and using a validation algorithm to resolve discrepancies, we significantly improve vessel detection, reducing uncertainty and ensuring effective maritime surveillance. Real-world testing has demonstrated the method's effectiveness in enhancing maritime security and enabling early threat response.

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Introduction

Aim and Scope

Monitoring and managing the maritime environment are crucial and challenging due to its vast size and continuously changing conditions[1]. Traditional surveillance methods such as land-based or ship-based observation, often fail to provide comprehensive and timely data over wide areas. In contrast, remote sensing data such as satellite imagery offer a significant advantage in addressing these challenges, due to their ability to cover large areas and capture high- and medium-resolution data.

The detection of vessels via satellite images can be enhanced by transmitters which provide information on the position, direction and other vessel characteristics, that can contribute to their detection. One of the most common tracking systems is the Automatic Identification System (AIS), which provides continuous information on the vessels' position. In addition to AIS, Long-Range Identification and Tracking (LRIT) was established as an international system by International Maritime Organization (IMO). Such tracking systems are present on most vessels, but in the case of smaller vessels (< 300 tons) do not need to carry AIS or LRIT[2]. In terms of satellite imagery, optical and SAR data are best suited for detecting vessels[3].

Regarding vessel detection using optical images, the main factors affecting the results are the size of the objects detected and the weather conditions. Vessels must span at least a required number of pixels in the image, depending on spatial resolution, while adverse weather conditions can negatively affect detection accuracy. Environmental factors such as waves, clouds and solar reflection can complicate the detection of vessels in optical images[4]. Moreover, white lines created by waves can look like vessels, confusing the algorithm. In contrast, detection is much more effective in calm seas. Additional, large clouds can cover significant parts of the image so detection may be impossible, while smaller clouds may appear as targets and need to be filtered out when classifying objects. In addition, solar reflection in waves can create high contrast areas in the image, which may be mistaken for vessels[5].

On the other hand, SAR data is a reliable method for detecting vessels at sea, as they provide good results regardless of weather conditions. Moreover, larger vessels, being metallic structures, reflect more radar signals. However, SAR images can have high levels of noise and sensitivity in the air, which can prevent accurate detection of vessels[6]. To create a reliable automatic vessel detection system, integrating data from multiple sources can yield more comprehensive and accurate results. Merging optical or SAR data with position point data such as AIS data, can serve as a verification system, enhancing the method's correctness and reliability.

This paper presents a methodology for processing EO data that combines OBIA with machine learning and deep learning techniques for vessel detection using SAR, multispectral images and RGB video. By integrating data from positioning systems (AIS), the processor provides in-depth monitoring and validation of results. The methods and technologies have been validated through real-world experiments, demonstrating their effectiveness in facilitating immediate threat response and enhancing maritime security.

Relative Literature Review

Since the first launch of optical and SAR satellites five decades ago, the number of satellites capturing images of the Earth has increased significantly. These satellites are classified by the spatial resolution of the images they receive to: very high, high, medium and low resolution. Among the open access satellite data, Sentinel satellites offer high-resolution images[7], while Landsat provides medium resolution data[8]. This categorization supports a variety of applications in environmental monitoring, resource management, and scientific research, leveraging recent advancements in satellite remote sensing technologies.

Recent research has focused on vessel detection in Sentinel-1[9-17] and Sentinel-2[18-22] images, often combined with other data types. For example, in a study[2], Sentinel-1 data with AIS datasets were integrated and a database and a web-based tool has been developed to detect dark vessels- not transmitting AIS signals, potentially involved in illegal activities and to visualize the vessel detections from both sources. Additionally, in another research a Polarimetric Combination-based Ship Detection (PCSD) method addresses challenges like speckle noise in SAR data, achieving an overall detection rate of over 85% and over 42% for small vessels[6]. Similarly, an algorithm using object detection methods on optical satellite images has been proposed for identifying small vessels, particularly those under 20 meters in length that typically lack AIS, with the capability of detecting vessels as small as 8 meters[23]. In addition to the Sentinel satellites, the Slovenian microsatellite NEMO-HD complements the Sentinel data with higher resolution multispectral and HD video data. With its advanced guidance, navigation and control system it can track non-linear tracks on-ground (monitoring coastlines) or point in a selected target on ground for up to several minutes [1-3]. Despite its high speed in orbit, NEMO-HD can maintain the orientation towards a selected area on Earth to record HD video. Video from space with motion tracking of vessels brings another dimension to the maritime traffic monitoring. These advancements in satellite remote sensing technology and data integration have significantly improved the accuracy and effectiveness of maritime monitoring and vessel detection.

Methods

Dataset

The EURMARS project exploits open access data and in particular, images from the Sentinel-1, Sentinel-2, Landsat-8/9 satellites and video from the NEMO-HD microsatellite for vessel detection. In the current work, only data from Sentinel-1, 2 and NEMO-HD satellites were used. Sentinel-1[24], launched in 2014, has a 12-day turnaround time and collects SAR images with a spatial resolution of 5x5 meters, ensuring high quality images regardless of weather conditions and time of day. On the other hand, Sentinel-2[25] provides high spatial resolution multi-spectral optical observations at 10x10 meters globally, has a 10-day retrieval period and features 13 spectral bands, making it suitable for various applications such as detecting changes in land cover, coastal monitoring, emergency management, border and maritime monitoring. NEMO- HD collects high resolution video in the visual part of spectrum and has the spatial resolution of 2.8x2.8 meters. The video footprint on ground is 3x5 km and can be taken globally. When the area of interest is within the reach of the NEMO-HD ground station located in Slovenia, the video can be downstreamed in real-time. For the other AOI's the video is saved onboard and transmitted to the ground during the next contact with the ground station in the same day.

For the training, testing and validation of the optical vessel detection model, four different datasets were used. The first one is the TGRS-HRRSD Dataset[26] (Figure 1) which contains 21,761 images acquired from Google Earth and Baidu Map, the second one is the Ship Detection from Aerial Images[27] containing 621 images of 1 class for the ship detection, the third dataset namely ship-detection[28] and the last one Ships in Google Earth dataset[29] which contain 794 Google Earth images and split into 2 groups – training and testing. All datasets are open access and contain optical images of vessels.

Figure 1: Sampe images from TGRS-HRRSD Dataset

Regarding the SAR image dataset used for training and testing of the algorithm, a labelled dataset with 102 Chinese Gaofen-3 images[30] (Figure 2) and 108 Sentinel-1 images used. The images cropped in smaller parts (256x256 pixels) creating 39.729 image chips.

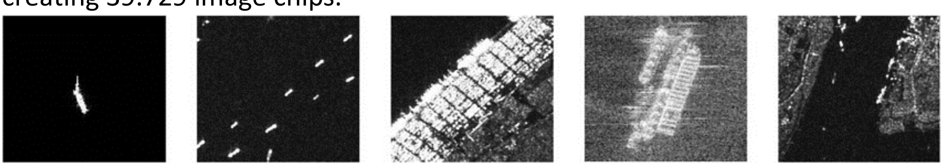
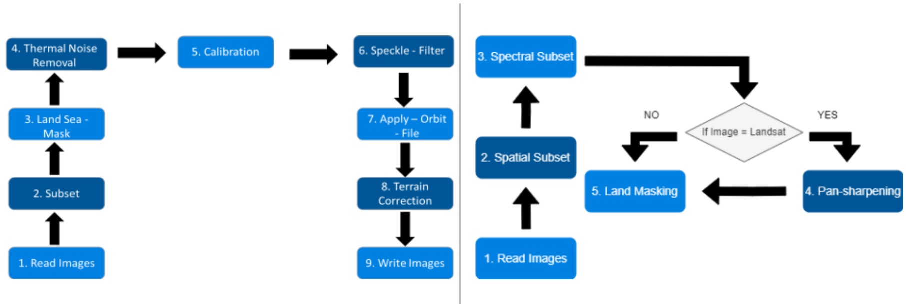


Figure 2: Sample images from Chinese Gaofen-3 images and 108 Sentinel-1 Datasets

Methodology

The vessel detection algorithm operates through several critical steps. First, it searches for new image products by continuously searching the Copernicus and USGS Earth Explorer product catalogue within a predefined region of interest for Sentinel-1, Sentinel-2 and Landsat 8,9 images. This search is performed on an hourly basis. An API facilitates the image acquisition process by allowing browsing of available products based on several parameters such as sensor type, product layer, region of interest, cloud cover and acquisition date.

Once an image is detected, the algorithm automatically downloads it and undertakes a series of pre-processing steps to optimize it for the detection algorithm. These preprocessing steps (Figure 3) are essential to ensure data quality in machine learning applications and include subset of images, noise reduction, masking to highlight the area of interest, and applying spectral or geometric transformations to prepare the image for accurate vessel detection.



(a) (b)

Figure 3: Workflow of the image dataset pre-processing (a) SAR, (b) optical imagery

The model, in order to operate the vessel detection, utilizes the YOLO (You Only Look Once) v7 algorithm for object detection, which has been pre-trained and tested for this purpose. Unlike traditional object detection methods which perform detection on various regions of an image, YOLO takes a different approach. It divides the input image into a grid and for each cell predicts bounding boxes and class probabilities directly within this grid. It resizes the input image to resolution of 448 × 448, and runs a single convolutional neural network on the image, that is consisted by 24 convolutional layers followed by 2 fully connected layers[31]. Although the YOLO model was trained on very high-resolution images, the algorithm was tested on high- and medium-resolution images. However, adjustments were made to ensure high training accuracy without negatively impacting the results. These adjustments include procedures such as scale invariance and data augmentation. Specifically, for scale invariance, the YOLO model was trained using images where the detected object's bounding box occupied 10% or less of the image area. If the bounding box covered more than 10% of the image, the image was discarded from the training dataset. A lot of repetitions were implemented in order the optimal batch size and epochs to be selected. Finally, the batch size was selected equal to 8 and the model seems to converge on 300 epochs.

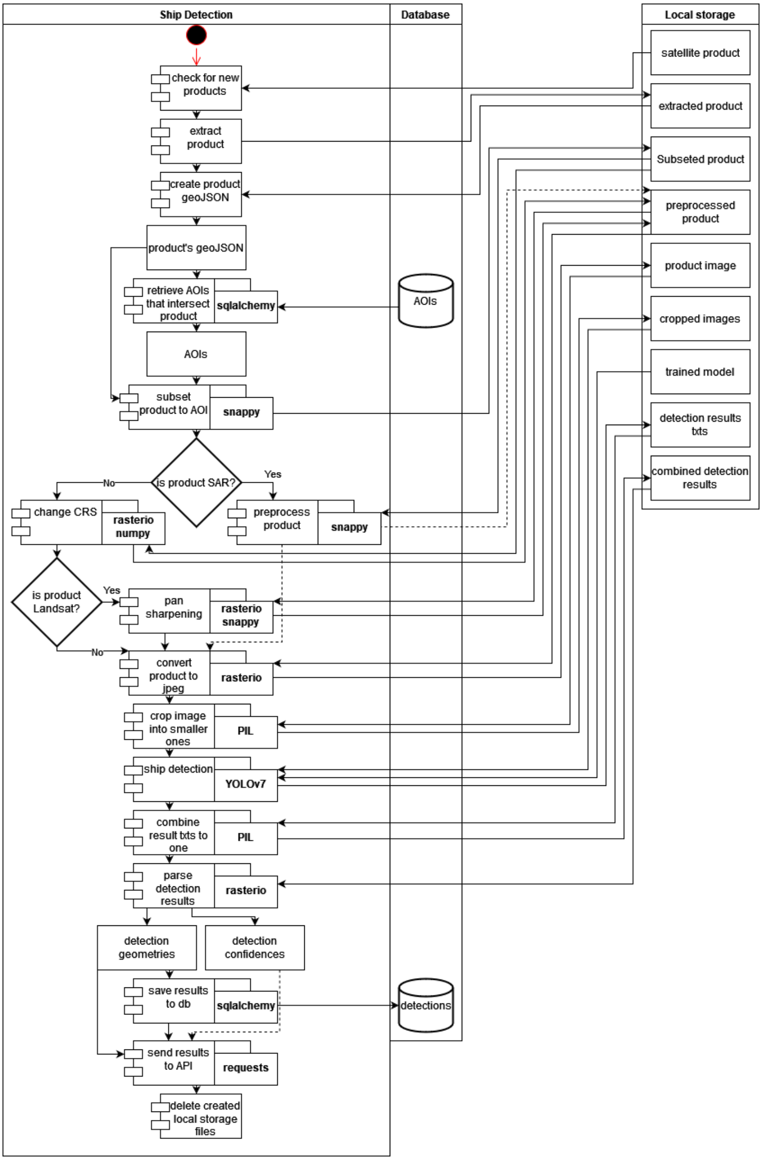


Figure 4: Algorithm Flowchart for vessel detection

Five metrics (objectness, precision, recall, F1 score and mean average precision) were used to evaluate the model during the training and validation processes in order to assess the effectiveness of the model in terms of how well the bounding box covers the detected object, the probability of a detected object appearing in a particular region of the image, the accuracy of the correct objects detected, the percentage of correct instances predicted, and the overall performance of the model.

The model identifies vessels by generating rectangular orthogonal parallels around them and annotating each one with a confidence level. The vessel identification process differs slightly between optical and SAR images. Figure 4 illustrates the flowchart of the algorithm, detailing the sequence of actions performed to extract vessel detection polygons from satellite images. The diagram includes each stage of the process, from image acquisition and preprocessing to the extraction of georeferenced polygons.

The algorithm for the vessel detection was entirely developed in Python 3.6 in the code user interface of Visual Studio and the libraries used for the processing are: Or, Tarfile, dotenv, Numpy, Rasterio, SnapPy, Geopandas, PIL, SQLAlchemy and OpenCV.

Fusion with AIS Data

AIS data can make an important contribution to vessel detection from satellite imagery as it provides real-time information on the position, speed and direction of vessels, which can be used to confirm and improve satellite detection. The methodology for the acquisition and exploitation of AIS data consists of the following steps. First of all, the data were acquired from ground-based antennas placed in the EURMARS study areas. After applying the object detection algorithm to a satellite image, bounding boxes are created around the detected vessels. The next step involves integrating the AIS data with the satellite images. During this step, the selected AIS data and the polygons from the detected vessels are projected on the image.

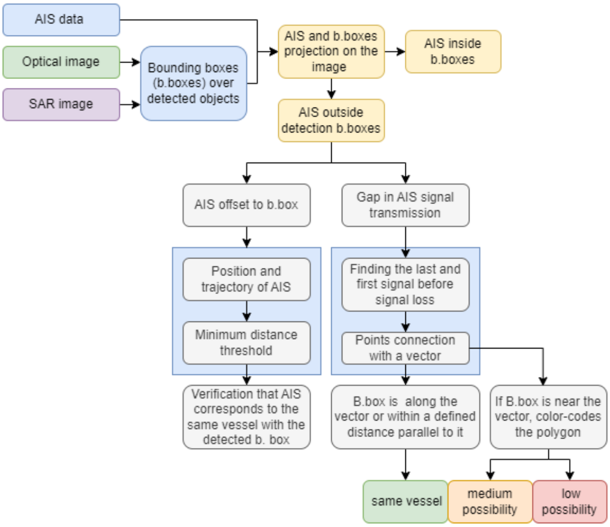


Figure 5: Flowchart of AIS-Validated Vessel Identification System

Then the detected vessel positions were verified by cross-referencing them with AIS data (Figure 5). This verification process determines which polygons from the detection algorithm contain AIS points (Figure 6a), thereby confirming the accuracy of the detected vessel positions. However, AIS data may sometimes display a positional offset relative to the detected vessel in the satellite image (Figure 6b). To address this, the algorithm considers both the position and trajectory of AIS points, applying a minimum distance threshold to ascertain whether the nearby AIS points and the detected bounding box correspond to the same vessel.

Additionally, the method addresses gaps in AIS signal transmission. If a vessel's position falls within such a gap (Figure 6c), the algorithm identifies the last known AIS point before the signal loss and the first point when the signal resumes, connecting these points with a vector (Figure 6d, 6e). The algorithm ensures that the detected vessel is located along this vector and within a defined distance parallel to it. If these conditions are met, the algorithm concludes that the AIS data and the detected polygon correspond to the same vessel, thereby ensuring consistent and accurate vessel identification despite potential data gaps. When the algorithm detects a vessel near the vector and needs to decide whether the detected vessel corresponds to the nearest vector, it color-codes the rectangle: orange for medium possibility and red for low possibility (Figure 6f).

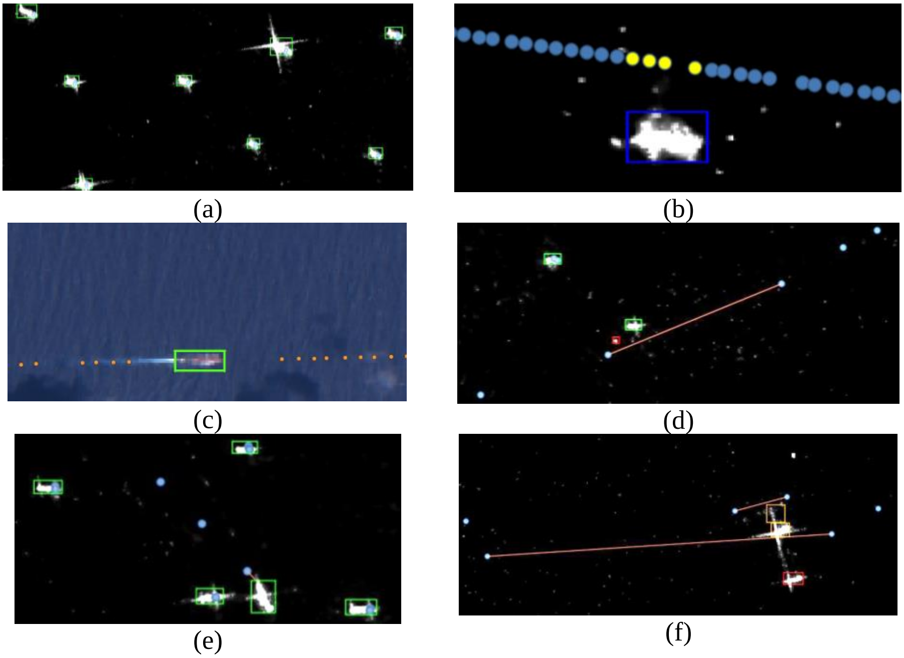


Figure 6: (a) Validated AIS points with detected vessels, (b) Offset of AIS data (c) Gap between AIS points, (d)- (e) Vector connection between successive points with temporal gap, (f) Detected vessels belonging to the vector

Results

Performance and Score

The model was trained, tested, and validated using multiple image datasets, with data distribution as follows: 80% for training, 10% for testing, and 10% for validation. The evaluation of results for both optical and SAR images was conducted using the metrics mentioned before. Figure 7 and Figure 8 illustrate the algorithm's performance over 300 epochs. Detailed results of the training and testing evaluations are provided below.

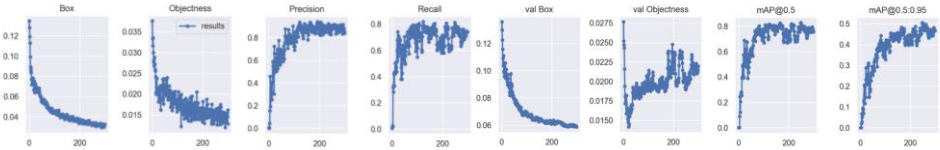


Figure 7: Training evaluation metrics of optical images

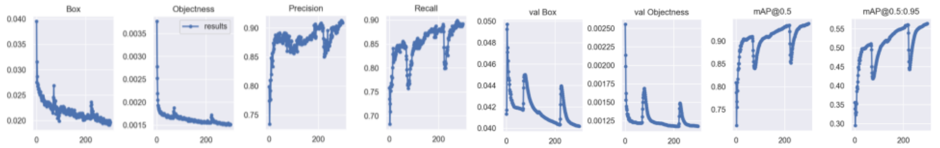
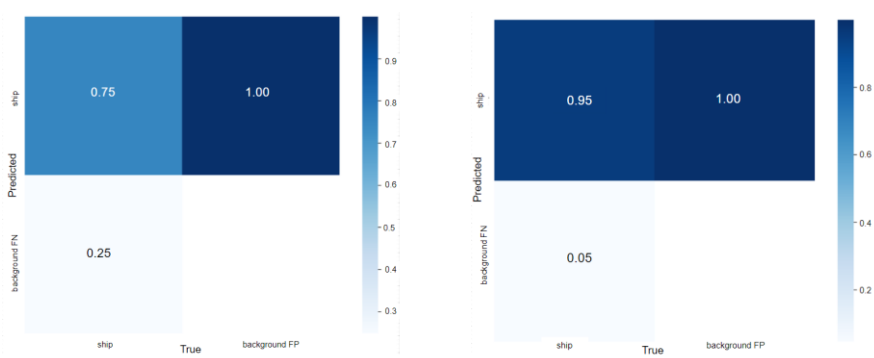


Figure 8: Training evaluation metrics of SAR images

Figure 9a displays the prediction accuracy for vessels in the optical images during the testing phase with a true positive rate of 75% for the "ship" class, while 25% of the predictions were classified as "background." Additionally in Figure 9b the confusion matrix shows the testing prediction accuracy for vessels in the SAR images. The model attained a true positive rate of 95% for the "ship" class, while 5% of the predictions were classified as "background."



(a) (b)

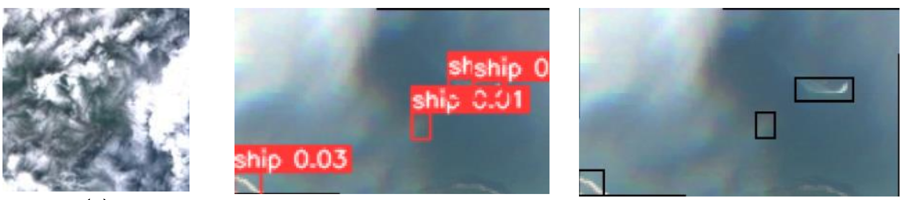
Figure 9: Confusion matrix for model testing for vessel detection in (a) optical images, (b) SAR images

Demonstration of the Pilot Use Case

During the EURMARS project, demonstration experiments were carried out to evaluate and validate the project's methodologies and systems. The project integrates a wide range of sensors, with the primary objective of enhancing the detection of sea objects through data fusion. Since several sensors from different locations can detect the same object, it was crucial to test these methods in real-time conditions, beyond simple simulations. This study specifically focused on merging satellite imagery and AIS data to improve detection accuracy at sea.

The first demonstration was held in Varna, Bulgaria on April 2024. During two days, the Sentinel-2 satellite passed over the area of interest on the first day, followed by the NEMO-HD satellite on the next day. Concerning the Sentinel-2 image, the cloud coverage was more than 90% but the area of interest was with light clouds (Figure 10a). NEMO-HD satellite collected a video with a duration of 1 minute over the area. During the video, the clouds were moving, causing some areas to appear cloud-free for a few seconds.

The algorithm implementation on the satellite image yielded one true positive and two false positives results (Figure 10b). Due to the dense cloud coverage, objects like small clouds are detected as vessels. Figure 10c shows the detection results occurred after the algorithm's implementation. Afterwards, the detected results are evaluated and the true positive detections are sent to the visualization platform, along with their metadata such as detection time, coordinates of the vessel and object's detected dimensions.



(a) (b) (c)

Figure 10: (a) Sentinel-2 image (b), (c) Detections on Sentinel-2

Moreover, on the NEMO-HD video, the algorithm made a vessel detection in a duration of 8 seconds with a confidence >0.025 (Figure 11).

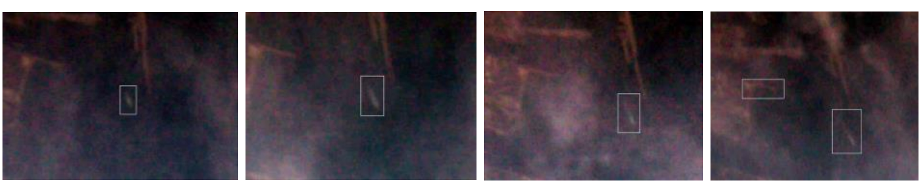
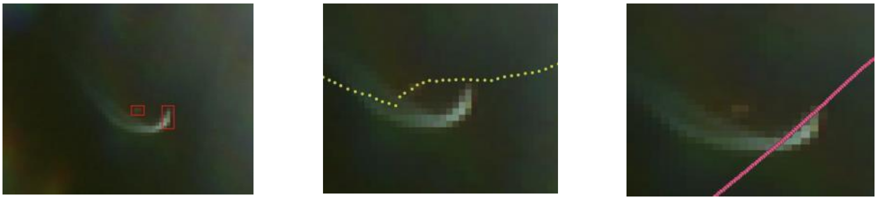


Figure 11: Detections on NEMO-HD video frames

To validate the detection results, vessel positions were recorded using two methods (Figure 12a). First, an AIS antenna was installed in the Varna region to capture and transmit vessel position signals as they passed through the area of interest (Figure 12b). Additionally, some GNSS tracker devices were given to the members of the vessels in order to record their position and as a consequence the position of the vessel (Figure 12c).



(a) (b) (c)

Figure 12: (a) Two vessels appeared on the image (b) Vessel 1 position with AIS (c) Vessel 2 position with GNSS tracker

A noted issue with the detected bounding boxes is that the algorithm occasionally misidentifies the wake of a moving vessel as part of the vessel itself, resulting in an overestimation of the vessel's size. Additionally, when two vessels are in close proximity, the algorithm may merge both vessels into a single bounding box. To address these challenges, the integration of AIS data can improve accuracy by providing additional information to distinguish between overlapping or closely spaced vessels, improving detection results.

Discussion

In this paper, an end-to-end methodology for vessel detection that integrates optical and SAR satellite imagery with AIS data was presented. This methodology automates the entire process from image retrieval to vessel detection, ensuring a continuous workflow without requiring user intervention. Initially, the vessel detection algorithm automates the search and acquisition of relevant satellite images, followed by pre-processing to improve the quality of the images. It then detects vessels within these images, providing a final output of detected vessels. The model demonstrates high accuracy in the validation phase, with a true positive rate of 75% for optical images and 95% for SAR images. Noticeably, the model works better for SAR images. The reason may be traced to the testing samples, which are more diversified for optical images. Compared in relevant works[32,33] where YOLO models were used for vessel detection, our model performs adequately, given the weather conditions that may affect the detection of vessels at sea.

The integration of satellite images with AIS data is a key element of our approach, facilitating the verification of vessel positions and allowing the identification of vessels that are either not transmitting AIS signals or experiencing temporary interruptions in transmission. The ability of the detection validation algorithm to manage and resolve mismatches between AIS data and satellite detections significantly enhances the accuracy and consistency of vessel identification. This capability not only improves detection accuracy but also reduces ambiguity in vessel position, thus saving time and minimizing uncertainty. In addition, the color-coding system effectively visualizes the confidence level of each detection, providing a clear assessment of how likely a detected vessel is aligned with the AIS data. This integration optimizes data use for maritime surveillance.

The implementation on real-world experiments in the EURMARS project exemplifies a robust approach to evaluating data fusion techniques for maritime object detection. The integration of various sensors, including satellite imagery and AIS data, underscores the importance of cross-referencing multiple data sources to improve detection accuracy. The demonstration in Varna, highlighted the challenges and successes of the project. Validation with AIS data and GNSS trackers ensured accurate verification, though issues with detecting vessel wakes and merging close-range vessels into a single bounding box indicate areas for improvement. These findings reinforce the value of real-time, multi-sensor data fusion in maritime surveillance and highlight the need for further refinement in the EURMARS project's vessel detection algorithm.

Conclusion and Future Work

In this paper, we introduced our work developed under the Horizon Europe project EURMARS, in which maritime object detection, more specifically, vessel detection was presented. A framework, in which YOLOv7 was exploited for object detection, integrates image acquisition, pre-processing, vessel detection, and result outputs for the purpose based on both optical multi-spectral images and SAR images. Four maritime datasets were used to fine-train the YOLOv7 models for optical images from a number of remote sensing satellites, whilst two datasets were employed for SAR images from two satellites. Validation and testing results have shown that the developed algorithms can achieve excellent vessel detection accuracy of 75% and 95% for optical images and SAR images, respectively. In the demonstration testing, Sentinel-2 (multi-spectral) images and NEMO-HD (RGB) video were captured in experiments associated with Automatic Identification System (AIS). In these tests, common errors of the system have been identified and corrected by modifying the developed algorithm. With more demonstrations throughout the EURMARS project, we will further explore robustness of the developed algorithm and enhance its resilience to deal with different scenarios in maritime environments. For vessel detection models, valuable training data may be generated from Sentinel-1, Sentinel-2 and Landsat, the targeted satellites, to increase the detection accuracy. We may also consider to modify the model architectures to fit better for maritime object detection, in light of scenarios with more tests in real-conditions.

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