Use of Sentinel-1 and Sentinel-2 for Monitoring Illegal Fishing Off Ghana

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USE OF SENTINEL-1 AND SENTINEL-2 FOR MONITORING ILLEGAL FISHING OFF GHANA

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ABSTRACT

An efficient and inexpensive service has been developed for the monitoring of fishing vessels in West Africa using Earth Observation (EO) data. The service makes use of fast-delivery data from the Synthetic Aperture Radar (SAR) instrument on Sentinel-1 and the Multi Spectral Imager (MSI) on Sentinel-2, detecting objects that differ markedly from their immediate background using a constant false alarm rate (CFAR) test. The selected objects are then discounted from further analysis if they fall within the bespoke land mask or can be shown from time series analysis to be static (signals associated with jetties, oil platforms and "ghost objects" arising from very bright land targets). Detections are matched to, and verified by, AIS data, which provides location and dimensions of ships that are legally in the region. Both matched and un-matched data are then displayed on a web portal for use by the Gulf of Guinea (GoG) state authorities.

Index Terms— *Synthetic Aperture Radar*, vessel detection, illegal fishing, automatic identification system

1. INTRODUCTION

Ghana, and other coastal countries in West Africa, are continuously affected by the adverse effects of Illegal, Unlicensed and Unreported fishing (IUU) in the region. IUU fishing poses a substantial threat to the conservation and management of dwindling regional fish stocks, causing multiple adverse consequences for fisheries, coastal and marine ecosystems, and for the people who depend on these resources.

However, there is now a growing desire to reverse the negative impacts of these human activities. Coastal states in the region now recognize the extensive benefits that the fisheries sector provides through trade in fishery products, employment and food security, and are collectively adopting innovative technologies to better manage the marine environment and its resources.

New initiatives to revive depleted fish stocks and improve the marine biodiversity within Ghana's exclusive economic zone (EEZ) and surrounds include the adoption of space-borne technology to augment existing monitoring and surveillance efforts. In Ghana, electronic monitoring of the fishing vessels operations, although backed by legislation, faces some challenges. For example, records of direct fishing and transhipment are only possible for vessels that participate in the vessel monitoring scheme of the Fisheries Commission of Ghana. The inability to detect and identify operations of non-cooperative vessels is a huge impediment in the fight against IUU fishing.

To address perceived deficiencies in fisheries management, the states' authorities and fisheries enforcement organizations need to have near real-time access to detailed information about fishing vessels illegally operating in Ghana

Here, we discuss the development and implementation of an integrated, EO-based service for surveillance of IUU fishing in the Gulf of Guinea. These activities were shared between Plymouth Marine Laboratory (PML) and ECOWAS Coastal and Marine Resources Management Centre (ECOWAS Marine Centre), based at the University of Ghana.

2. VESSEL MONITORING SERVICE

A new service was developed for monitoring fishing vessels in near real time (NRT) using EO data. The service benefits from using both active microwave and optical remote sensing data provided by Sentinel-1 SAR and Sentinel-2 MSI sensors, respectively. By cross-checking the remote sensing observations with information obtained from the Automatic Identification System (AIS), non-cooperative fishing vessels were revealed and reported via the web-based Geographic Information System known as the web portal.

The service processing chain manages multiple processes in a scheduled, automated fashion, including: database creation/backup; checking of new scene availability; scene downloading and staging for processing; scene calibration, masking and mapping; vessel detection; checking of AIS data availability; AIS data ingestion; vessel matching; image generation, statistical reporting and staging for portal visualisation.

The processing chain interfaces with the ESA Sentinel catalogue via the Copernicus API hub (https://scihub.copernicus.eu/apihub/), querying the availability of new scenes from Sentinel-1 and Sentinel-2 data. It also ingests AIS databases, delivered via FTP from the University of Ghana. The processing chain, which is predominantly written in python, runs every hour.

The ordering and scheduling of processing chain tasks is managed by a centralised SQLite database, which stores a set of keys against the required stages, as well as metadata on the progress of a given scene through the chain. This metadata also includes status information on the success of each stage, and error information in the case of stage failures.

2.1 Vessel detection in Sentinel-1 SAR data

Initially, the service was constrained to cover only the sections of the Ghanaian EEZ closest to shore, limited by the SAR coverage of Sentinel-1A. However, recent augmentation of Sentinel-1A coverage with Sentinel-1B scenes helped to address this limitation, giving more extensive coverage in the offshore environment.

The images are acquired predominantly in interferometric wide-swath (IW) mode and dual polarisation (VV+VH). The block-diagram in Figure 1 shows the main stages of vessel detection in Sentinel-1 images. The Level 1 ground range detected (GRD) products were initially pre-processed to remove thermal noise and image border noise and to calibrate measurements. The images were mapped into geographic coordinate system and then cropped to cover only the area of interest. Next, the land pixels were masked out and eliminated from further processing by flagging them as invalid. To improve the accuracy of land masking the land/water mask was generated from a set of Sentinel-1 images covering a period of one year. To generate this mask the images were merged and a threshold was applied to discriminate between water and land pixels.

A two-stage algorithm was developed for vessel detection in SAR images. Firstly, the images were pre-screened using a constant false alarm rate (CFAR) detector [2] to identify the objects that differ substantially from their immediate background (see Figure 1). A multiplicative model of image speckle has been adopted for CFAR threshold selection. The parameters of this model were estimated using order statistics method [1].

The VV- and VH-polarisation SAR images were processed by CFAR detector separately and two statistically independent detection results were generated. The dual-polarisation data were then combined to reduce noise and improve accuracy [2].

At the second stage of the detection algorithm the contours of detected objects were retrieved from the binary data and the connected components were labelled. Each of these components represented a group of vessel pixels and was processed separately to estimate vessel coordinates, heading, length and width. To suppress the effect of side-lobes in the SAR image and improve the accuracy of parameter estimation, a morphological image filtering technique has been applied [3]. The structuring element of the morphological filter was adaptively selected using vessel dimensions and orientation parameters, preliminary estimated using image moments [3]. After image filtering, the refined length and width parameters were estimated using the offset centre of gravity method. To reduce false alarms from the CFAR detector the estimated length and width parameters were compared with the values, known a-priori from the analysis of AIS data. Next, the static objects (those without changing location) were identified by recording and comparing the location of all detected objects within one month interval [4]. The static objects were associated with SAR "ghost objects" arising from very bright land targets, oil platforms or small patches of land, and were discarded as false alarms.

The normalised radar cross-section (NRCS) profiles of the remaining detected objects were characterised by estimating the number and location of bright spots. These features were used to assist in the discrimination of fishing vessels and in the identification of trans-shipment scenarios when the illegally caught fish gets transferred between vessels.

Figure 2 shows an example of vessel detection in Sentinel-1 image of Port Tema in Ghana. This is a challenging scene for the detection algorithm due to the high concentration of vessels waiting at the entrance to the port.

2.2 Vessel detection in Sentinel-2 MSI data

Application of Sentinel-2 MSI image for vessel detection in GoG was mostly limited by the presence of clouds. For this region, the cloud coverage may reach 75-80% in late autumn and winter periods [5]. Despite that, multispectral optical data are useful in support of the observations delivered by Sentinel-1 SAR sensor.

A block-diagram of Sentinel-2 MSI data processing algorithm is shown in Figure 3. The Level-1C MSI data were first processed by Sentinel-2 atmospheric correction algorithm (Sen2Cor) and the bottom-of-atmosphere reflectance images were generated.

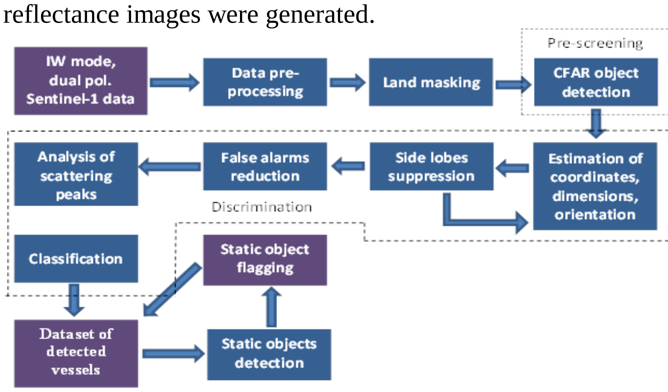


Figure 1. Sentinel-1 SAR vessel detection algorithm.

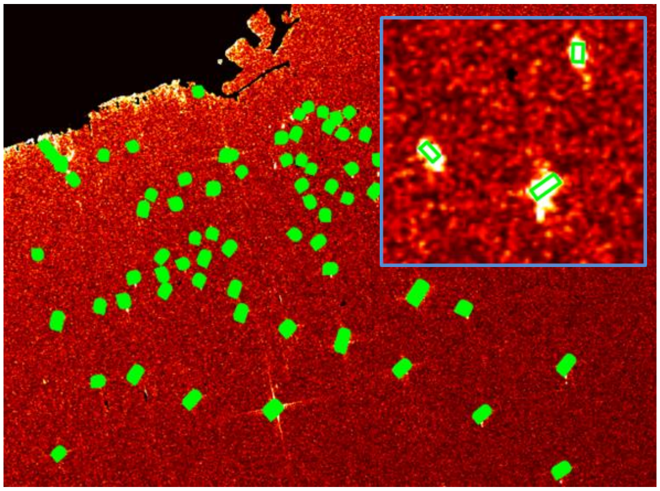


Figure 2. Automatic vessel detection in Sentinel-1 SAR images. The backscatter intensity is shown using red palette.

After atmospheric correction, the images were resampled to 10 m spatial resolution and cropped. Then, open water areas were outlined through land masking. Next, the image was split into tiles and each tile was processed separately, in parallel.

Pre-screening of MSI image in Figure 3 was carried out using the RX anomaly detection algorithm of Reed and Yu [6]. However, this algorithm failed to discriminate vessels from small clouds. It also generated false alarms at the edges of contrast objects, such as between water and clouds. To reduce false alarms, image pixels were classified into open water and cloud categories using the cloud mask generated by Sen2Cor atmospheric correction algorithm. Then, the spectral content of the images was transformed into the principal component (PC) space. The parameters of the PC transformation were preliminarily estimated from data masked as open water. The RX algorithm is then applied to detect anomalies. The connected anomaly pixels were grouped and each group is processed separately. For each group of pixels, a bounding rectangle was calculated, and the coordinates, dimension and orientation parameters were derived from its corner coordinates. A group of anomaly pixels was flagged as a false alarm if its estimated length or width was smaller or larger than a possible vessel size. This way the large clouds incorrectly identified at the pre-screening phase were removed.

Spectral analysis was applied to identify small clouds and other false alarms in the detected data. Accordingly, the difference between the spectrum of detected anomaly pixels and the background spectrum was measured and compared with the threshold value. To describe the background spectrum, we used a two-component linear mixture model. In this model, the spectrum was presented as a weighted average of the open water and clouds spectra [7]. An example of vessel detection in a Sentinel-2 image is shown in Figure 4.

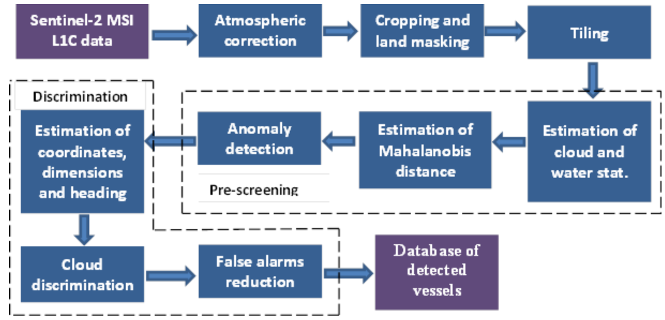


Figure 3. Sentinel-2 MSI vessel detection algorithm

2.3 Matching vessels in satellite images and AIS data

In order to match AIS vessel positions to satellite detections, vessel tracks were bilinearly interpolated in time using a Centripetal Catmull-Rom Spline (CCRS) function [8]. This approach takes into account the heading of the vessel as recorded at each point, producing an interpolated ship track. The CCRS function was built using all AIS points from 2 hours either side of the satellite overpass. Where insufficient points exist to build the CCRS function, linear interpolation was used.

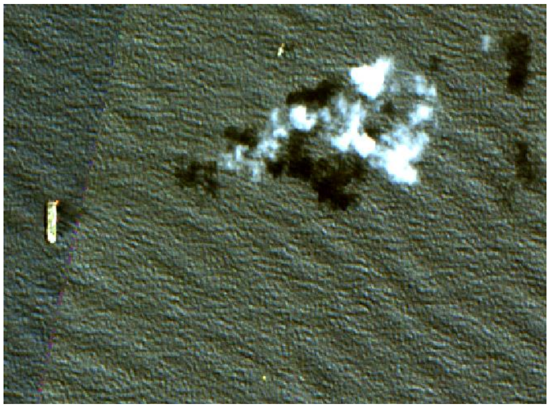
The catalogue of interpolated AIS vessel positions was sequentially compared with the catalogue of satellite vessel positions, with each satellite-detected vessel retaining a potential match-link to all AIS vessels that fall within a radius of influence. The radius was determined based on the maximum potential speed of the vessel and the time interval. All vessels outside this radius are discarded as matches.

In vessel-dense environments, sequential matches based on n-dimensional proximity may not yield the optimal solution. To solve this problem, the match assessment was performed repeatedly (by default 10,000 times), with the vessel selection sequence made at random. The total n-dimensional score of all matches made for each iteration was retained and the lowest score (indicating the best matching) was recorded. Leaving potential candidate vessels unmatched biases the system to a high score, ensuring that vessels are preferentially matched.

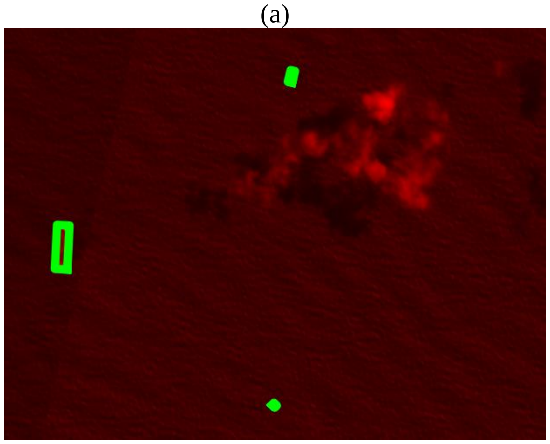
3. RESULTS

A prototype demonstration of the developed vessel monitoring service has been run in the EEZ of Ghana, West Africa. A proof of concept using Sentinel-2 MSI data for vessel monitoring has been successfully evaluated using test scenes and demonstrating high efficiency even for data severely affected by clouds. The processing chain for Sentinel-2 data is currently in the testing phase.

Validation of Sentinel-1 SAR ship detection algorithm was performed by comparison with AIS vessel signals to ascertain how many ‘expected’ vessel signatures were detected in SAR imagery. The results of this analysis are shown in Table 1.



(a)



(b)

Figure 4: Vessel detection by Sentinel-2 MSI sensor: (a) RGB image; (b) detected vessels shown in green

It has a 91% success rate at detecting AIS vessels in the region. The statistics in Table 1 are not corrected for the potential prevalence of 'false' AIS vessel signatures, which have no SAR signal and would remain unmatched. Figure 5 shows the distribution of SAR to AIS match distances over a 15 month period. 75% of matches are made at 300m distance or less. For the small proportion of matches distances >1000m have been observed. As no quality control of the AIS data was performed, these occurrences of errors could be caused by AIS 'tricking' that allows many vessels, apparently equipped with AIS systems, to avoid detection [9].

4. CONCLUSIONS

An automatic system has been developed to use optical and SAR-based approaches to detect shipping in the Ghanaian Exclusive Economic Zone, match those co-ordinates with information on known registered shipping, and provide the authorities with timely information in order to investigate the unregistered vessels. The procedure has a high success rate, detecting 91% of registered vessels, and a fast throughput, processing and delivering information within 1 hour of the ingestion time.

Table 1. Detection and matching results for all recorded vessels for Jul. 2016 to Dec. 2017

Vessels with AIS during analysis period	1924
Vessels detected in SAR	1742
SAR detections missed	182
Percentage detection success (%)	91
Median distance between AIS/SAR detections (m)	100
Mean distance between AIS/SAR detections (m)	1130

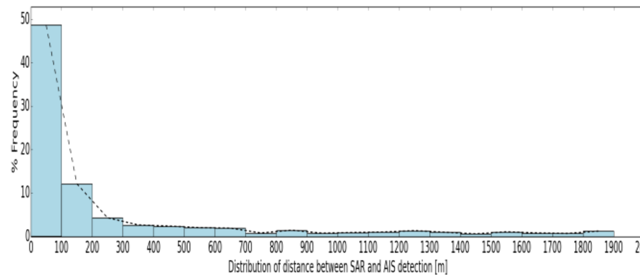


Figure 5. Distribution of distances between SAR-AIS vessel matches for 01/07/2016 to 01/11/2017

5. ACKNOWLEDGMENTS

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