A vessel risk framework to identify vessels involved in illegal, unregulated, and unreported fishing

a technical guide...

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Abstract

Data science is increasingly being applied to optimise, or improve operations in business and industry. There is also a movement gaining popularity to apply data science approaches to solve problems relating to social good, for example in environmental, healthcare, or government services. A framework is here outlined that demonstrates an approach to improve detection of illegal, unregulated, and unreported (IUU) fishing using multiple data sources. Automatic identification system (AIS) data was used to predict whether a vessel is fishing, and generate components to indicate the likelihood of a vessel engaging in IUU behaviours. These AIS data were then correlated with satellite imagery and vessel images extracted. This document describes the data sources relevant to this problem, the approach taken, as well as evaluation of our methods, and future work.

Contents

1 Introduction

Every year around 26 million tonnes of seafood worth close to $24 billion are extracted from the planet's oceans by illegal, unreported and unregulated (IUU) fishing. These IUU fishing techniques include: extracting fish from waters of other nations or designated marine protected areas, catching fish using illegal and ecologically damaging techniques, or under-declaring fish by transshipment at sea. Such practices are especially rife in the rich tropical waters of Southeast Asia due to the burgeoning demand in the region, and challenges of enforcement. This project sets out to address the problem of IUU fishing by correlating multiple data sources, and using data science techniques to identify vessels involved in IUU fishing.

Overfishing and IUU fishing have lead to huge declines in fish stock and some species such as tuna have declined by over 90%. Our project partner the World Economic Forum (WEF) is committed to improving the state of the world by engaging business, political, academic, and other leaders of society to shape global, regional, and industry agendas. In particular the WEF promotes initiatives to improve ocean governance, food chain sustainability, and environmental conservation.

In partnership with the WEF this DSSG Europe project has set out to create an open-source tool combining multiple data sources to help combat IUU fishing. This proof-of-principle study of fishing in the Torres Strait aimed to demonstrate how data aggregation from sources such as satellite imagery, synthetic aperture radar (SAR) and automatic identification systems (AIS) can be correlated and used with data science methods such as object recognition and anomaly detection to aid in identification of illegal fishing. This data science approach to detecting IUU fishing could ultimately improve enforcement, guide governance, and inform policy decision making.

There are many challenges associated with detecting IUU fishing. Firstly, the world's ocean comprise the majority of the EarthâĂŹs surface (71%). This is a large area to inspect and hence the volumes of data involved are large. There are many vessels in this large area relating to commercial, leisure, or fishing activities. Systems to detect and track these vessels such as automatic identification systems (AIS) tend to be implemented nationally in vessel management systems (VMS), hence there is little standardization of the data format. Satellite data on the other hand is relatively infrequent, can be obscured by cloud cover, and may not have good coverage in the ocean. Combining these data sources can be difficult to find appropriate images and AIS data. There is also a distinct lack of high-resolution open-source data sources in this domain, due to the cost of data collection.

A socially desirable outcome for this project would be to successfully demonstrate how these data can be used to identify IUU fishing. In partnership with the WEF and organisations this can be conveyed to policy and decision makers to expand the study. A socially desirable outcome would be to improve detection of illegal fishing via these data sources, a secondary outcome of this would be to provide improved enforcement of illegal fishing, which in turn would improve regulation as it becomes harder to evade capture. The result of this would be to promote more sustainable fishing practice and environmental conservation.

2 Previous work

3 Data sources

3.1 Automatic identification system (AIS)

Vessel location for the period from May 2016 to June 2017 was captured using the Automatic Identification System (AIS) transponders installed in every vessel with a length greater or equal to 30 meters. These transponders broadcast two types of messages. First, they transmit positional signals every 10 seconds, reporting GPS coordinates and navigational features of the vessel (i.e., speed, course, and heading). The second type of message is static and reports constant features of the ship, such as name, callsign, length, and destination.

Beacons near the shores capture these messages, working as an avoiding collision system with the sea coast and other vessels. This makes AIS an important component of maritime security (Tetreault, 2005). Coastal receivers do not always capture AIS signals away from shore.[1] Nonetheless, we use satellite captured AIS signal provided by Spire; this allows us to retrieve vessel tracking data from all over the world, and not only from vessels near seashores.Some caveats arise with the use of this source. First, AIS signals fetched by satellites can *bunch together* bunch together leading to data loss, since the satellite is only able to process a limited number of signals at a time. Second, accuracy is not always certain. Hence there is a possible measurement error in the location and other features of the vessels. Lastly, there is the possibility of AIS tampering in vessels involved in illegal activities, such as UUI.

3.2 Satellite imagery

To account for a visual validation of the AIS data, we used different sources of proprietary satellite imagery for the same timeframe of the positional AIS data. We rely on two sources of high-definition satellite imagery. The first source is Digital Globe (henceforth GBDX) which reports images with visual and Near Infrared (NIR) bands with a resolution of $\approx$ 3 meters per pixel. Second, we used imagery from Planet, which has higher revisit times that GBDX, but at the cost of lower resolution (from $\approx$ 10 m. to $\approx$ 3 m. over the equator).

Images from both sources were orthorectified and projected into a common grid. The first process corrects possible terrain distortions due to higher elevation angles. [2] The second process projects the images into a common grid to georeference the images into a common grid, usually under a *UTM* local projection. Despite the availability of more advanced image processing tasks, as *Pansharpening* or *Atmospheric compensation*, we decided to use a single approach. Also, some advanced image processing tasks merge visual and Near Infrared Bands, hindering the use of a multispectral or thermal analysis.

4 Approach

We used the best approach

5 Evaluation methodology

evaluate this

6 Future work

Lots will be done in the future

[1] According to Spire, the coastal receivers can only capture data in an 80 kilometers range.

[2] This angle is commonly known as Nadir. The terrain displacement occurs when satellite sensors are not orthogonal to the earth terrain. Thus the optimal Nadir angle is 90°.

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References

Tetreault, B. J. (2005, sep). Use of the Automatic Identification System (AIS) for maritime domain awareness (MDA). In *Proceedings of oceans 2005 mts/ieee* (pp. 1590–1594 Vol. 2). doi: 10.1109/OCEANS.2005.1639983