A Review on Detecting Suspicious Fishing Activity

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Abstract - According to the UN Food and Agriculture Organization, illegal, unreported and, unregulated fishing is culpable for the loss of more than 26 million tonnes of fish each year. This means that approximately 20 percent of the world's seafood is caught illegally and consumed by citizens globally, who are unknowingly contributing to an illegal industry worth about 20 billion USD every year. The ecological losses of these activities are far greater than the financial ones and put a number of species in danger due to overfishing and fishing in Marine Protected Areas (MPAs). Thus the need for much more sophisticated global surveillance and enforcement has increased. This document outlines the current status of research and progress in developing unique and state-of-the-art techniques for the detection of suspicious fishing activity with the help of the Automated Identification System (AIS), Vessel Monitoring System (VMS), real-time satellite imagery, and deep neural networks. This review will provide researchers with knowledge about some of the current methods used in detecting fishing activity which they can build upon for future works and work on further improving this field.

Keywords - fishing activity, AIS, global fishing watch, illegal, unreported, unregulated, Flag of Convenience, neural networks

1. INTRODUCTION

Suspicious fishing activity or Illegal, Unreported, and Unregulated fishing (IUU fishing) is a worldwide issue that threatens ocean ecosystems and sustainable fisheries. Illegal fishing is the kind of fishing conducted by foreign or national vessels in the waters that are under the jurisdiction of a country or an organization, without the permission of the said country or organization. Unreported fishing is the kind that has not been reported or misreported to the authorities. Unregulated fishing is the kind of fishing that takes place in areas with no conservation or management measures for fishing activities[1]. It happens all around the globe from the high seas to the exclusive economic zone (EEZ), which is a 200-mile band from a nation's coast wherein they have full jurisdiction over the exploration of marine resources. According to the UN Food and Agriculture Organisation (FAO), IUU fishing accounts for 26 million tonnes of fish caught annually[2]. Fisheries are an important part of food sources and employment all around the world but these fisheries are being compromised heavily by IUU fishing activities. IUU fishing is a pressing matter that endangers local fisheries and can harm the local food supply.

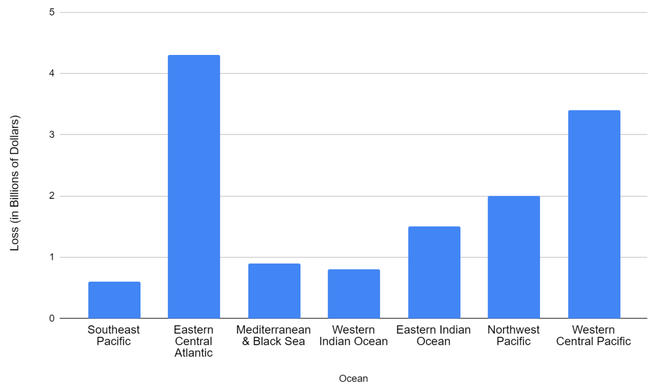

Fig 1. Loss in billions of dollars for every ocean.[11]

2. DETECTION USING AIS SIGNALS

The Automatic Identification System or AIS is an automatic tracking system used for tracking vessels and avoiding collisions. AIS is a radio system to broadcast and receives a Maritime Mobile Service Identity along with the ship's velocity and current position. But, now AIS is being viewed as a tool that doesn't only help prevent the collision of ships but also as a tool that can be used to detect fishing activity[3]. The Global Fishing Watch is a partnership with Oceana, SkyTruth, and Google which collects, analyzes, and documents the AIS data. They have made the data publicly available so that anyone with an internet connection can track any vessel around the world[3]. The International Maritime Organization requires AIS transceivers to be installed on all vessels of 300 gross tonnages and upwards which undertake international voyages, cargo ships of 500 gross tonnages and upwards not undertaking international voyages, and all passenger ships irrespective of size[4].

Fishing vessels can be broadly classified into two types - trawlers and non-trawlers. Trawlers use nets or trawls which are dragged by the vessel underwater at a certain depth, speed, and pattern of movement to keep the net taught and to catch fish. Non-trawlers consist of longliners that have a long main line that has baits at certain intervals, seiners that move at high speeds to catch fish that are near the surface of the water using seine nets, etc. All these vessels have a certain trajectory that can be mapped using the AIS data, which further helps to identify the vessel type and link it to the vessel's Maritime Mobile Security Identity (MMSI) number. This is very useful if the vessel tries to hide its identity and engage in dark fishing. So, after finding out the vessel signature the vessel can be flagged for potential suspicious fishing using zonal coordinates, temporal variations, and vessel tracking[5].

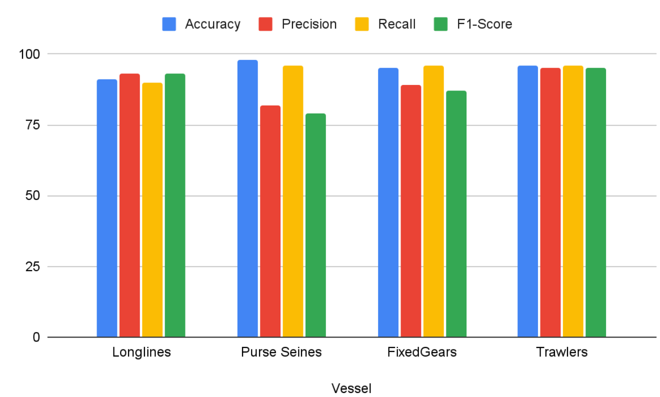

Fig 2. The accuracy, precision, recall, and F1-score of classification of vessels based on their movement[5]

AIS signals coupled with deep neural networks can be a powerful tool in the detection of IUU fishing activity. The position data from these signals can be used to lay vessel tracks and predict trajectories for possible intersections with Marine Protected Areas (MPAs). Historical data can be used to lay vessel tracks for certain classes of vessels. Any aberrant behaviour in those classes of vessels can then be further analysed for suspicious activities.

Vessel trajectories can also help uncover illegal transshipment activities. Transshipment refers to the shipment of goods or containers to an intermediate destination, and finally to another destination. Fishing vessels are required to report encounters with other fishing vessels. Upon analyzing vessels if two ships are found to have been at the same point at the same time but failed to report such an incident, there is a high likelihood of them being engaged in illegal transshipment activities[6].

When equipped with satellite imagery, a deep R-CNN (regions with convolutional neural networks) can be used to classify vessels and match them with their AIS data. Then an LSTM (long short-term memory) based Neural Network can also be used to analyze the classified vessel's track and detect whether it is fishing or not. If a certain image has been classified and is also detected to be fishing but there is no associated AIS, it is likely to be engaged in IUU activity. Furthermore, the probability of that fishing vessel being dark becomes closer to one when ships in the same region are transmitting AIS. This rules out the possibility of low connectivity in that region as AIS from other ships is visible[6].

Vessel classification is important for detecting fishing activity but a 3-stages algorithm proposed by the authors in [7] does not need the type of the vessel, to differentiate fishing activities from non-fishing ones. Trajectory reconstruction is followed by segmenting the trajectory in small windows which are used to label the data, and then finally using Convolutional Neural Networks to predict the fishing status for some time window in the trajectory[7].

First, the authors reconstructed the trajectory of a vessel by using the data generated by the AIS transceiver. Learning from AIS data is no mere feat as there are massive amounts of data that need to be pre-processed. The trajectory reconstruction process handles a variety of challenges like cleaning the data of unwanted noise or exceptional instances[7].

Next up, they classified the data by using a sliding window segmentation method to partition trajectories into short segments, which are labeled based on the probability of whether they were engaged in a fishing activity. As fishing activity is generally considered to be a patient activity that extends over considerable time periods from several hours to even days based on the fish you want to catch. Feeding a classifier model with huge data might decrease the performance but also increase the complexity of the model. So, to tackle this problem the trajectory is fragmented into segments using a sliding window which helps simplify the dataset and improve the model's performance. After this, a majority voting scheme is applied to classify the extracted sequences. However, as fishing vessels do not frequently switch their status from fishing to non-fishing and vice versa, the majority of window sequences are pure fishing or non-fishing cases[7].

And finally, the vessel status will be determined based on the majority of labels assigned to the selected segments of the trajectory of the vessel. For this, a convolutional neural network is used whose output is a binary label that determines the fishing status of the vessel[7].

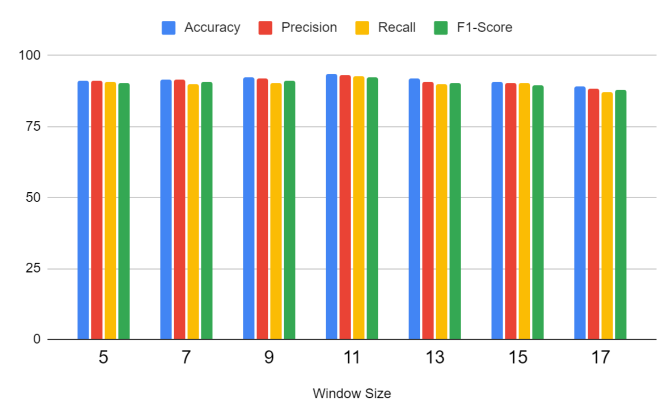

Fig 3. Performance of the model for different window sizes of the trajectory[7]

Another method for detecting IUU fishing Activities involves three main steps. The first step includes the identification of the endpoints, followed by segmentation of End-To-End trips, and then finally, ranking the suspicious activity of the vessels[8].

Endpoints are extracted by identifying the vessel's anchorage points, anchorage points are where the vessels remain stationary for long periods of time, after identification these points are clustered. The list of endpoints includes all the main ports as well as non-essential and lesser-known harbors [8].

After clustering of anchorage points along with the identification of endpoints, the vessel's trajectory is segmented into end-end trips from one end-point to the other as mainly all the fishing vessels follow a certain routine as their trips usually begin and end at an anchorage point. A vessel can have three types of trips: transition trips, searching trips, and fishing trips which can be determined by the length of the trip[8].

Then the vehicle suspicion score is calculated which is the aggregate of all the trip suspicion scores combined for all the trips of a vessel for that year. The trip suspicion score is the sum of the global anomaly score and the local anomaly score. The global anomaly score is a measure of the deviation of a particular vessel's behaviour in comparison to the behaviour of other vehicles while the local anomaly score is the measure of the vessel's anomalous activities during the trip in question. A minimum threshold of going dark for a vessel can be set to potentially identify suspicious fishing activities. For ranking and profiling the vessel's activities - first, the vessel suspicion score is studied and observed over time, this gives us an understanding of the vessels engaged in suspicious activity and their similarity with each other in terms of consistency[8].

A spatial pattern can also be created to study the behavior of more suspicious vessels in comparison to normal vessels wherein grids are applied. Each grid cell can be classified into 3 sets: white cells, grey cells, and black cells where the majority of the AIS-obeying vessels are in the white cells, followed by the grey cells and the rest are in the black cells. A white cell can be an area where a vessel cannot have an excuse to turn off its AIS transmitter whereas a black cell can be an area with disturbance such that AIS signal transmission is weak. It is observed that more than 70% of vessels in the white cell are sending active AIS responses and a range between 30-70% are sending AIS signals in the grey cell and less than 30% of vessels send AIS signals in the black cell. A strong behavioral pattern can be deduced by spatial differentiation as 82% of vessels that went dark in white cells have been classified as more suspicious followed by a 77% and a 63% in grey and black cells respectively[8].

Cell Type	% of vessels sending AIS signals	% of Dark vessels Being suspicious	Possibility of IUU activity
White	>70%	82%	Low
Grey	70-30%	77%	Moderate
Black	>30%	68%	High

Table 2: Comparison of Data found between different types of cells[8]

3. DETECTION USING VMS

Vessel Monitoring System or VMS is used by vessels that engage in commercial fishing. They are used to track potential illegal fishing activities. VMS is used to improve the management and sustainability of fisheries by ensuring that vessels follow the rules and regulations.

The primary function of VMS data is surveillance, and polling frequency varies greatly amongst fisheries. By connecting trawl position with logbook catch data, VMS data may be used in population-depletion analysis to further define fishery assessment model parameters and estimate population size. Finding the lowest polling frequency that can accurately describe the trawl track without significantly biassing results is crucial[9].

It is likely that catch-per-unit-effort (CPUE) is not proportionate to total biomass if prawn trawling is concentrated in regions with high target species abundance. This could go against the management's advice that is given in consideration of the species evaluations[9].

Gear saturation is another factor that affects the CPUE. Therefore it is of extreme importance to accurately identify the trawl tracks without much error[9].This can be accomplished by comparing the GPS-derived tracks with simulated VMS fixes obtained at various polling frequencies. Following that, data from high-polling-frequency VMS (HPFVMS) can be used to determine trawling intensity. Once this has been determined, a population-depletion analysis can be performed by matching the vessel logbook catch records with the trawl tracks. However, due to the HPFVMS data's coverage being insufficient, it is necessary to add the standard-frequency VMS data to the data set[9].

Each track can be classified into 3 categories: the area that would be covered by trawling between subsequent points if it were done in a straight line (TA), the area of track referenced once only (AP1) and the ratio of the AP1 to the corresponding track area (PAP1). The speed of the vessel is assumed to be constant[9].

The accuracy is calculated in contrast to 1-min Polling Interval, assuming it to be precise as feasible. The findings demonstrate that the track area is consistently underestimated by all simulated polling intervals and that the error grows in proportion to the Polling Interval. The estimates at a 30-min polling interval are roughly 72.5% of the actual track. At 20-min, about 82.5%, and at 1-hour Intervals, about 55%. The estimations, however, are only 30%–40% of the true track at 2-hour intervals, and there is a significant loss of precision[9].

The trawl tracks made by the vessels in areas of intense fishing, may be correctly represented using HPFVMS. The polling frequency, however, imposes a limit on the approach's accuracy. Because trawlers are unlikely to move in straight lines between polling locations at low polling rates, a straight-line linear interpolation may result in inaccurate estimates. Moreover, high polling frequency data collection can be quite costly[9].

However, combining high and low polling frequency data together seems to be a plausible solution to enhance the accuracy of the analyses while keeping the costs down. There will be a wider spectrum of applications where this data can be useful[9].

Polling Interval (In min)	**Ratio of the mean of AP1 to the True mean (at 1 min Polling Frequency)**	**Ratio of the mean of Track Area to the True mean (at 1 min Polling Frequency)**	**Mean Accuracy**
1	1	1	100%
10	0.9	0.9	90%
20	0.8	0.85	82.50%
30	0.7	0.75	72.50%

60	0.5	0.6	55%
120	0.3	0.4	35%

Table 3: Mean Accuracy at different polling intervals[9]

Another method of detecting possible IUU behavior is to identify Flag of Convenience (FOC) vessels. Flag of convenience vessels is a common practice among vessel owners wherein they enlist their ships in countries other than their own. They often register their ships in countries where registration processes are quick, taxes are low, and rules and regulations are almost negligible. FOC vessels are generally part of dark fleets and are most likely to engage in IUU activity[10].

VMS signals are mandatory for vessels entering into the Regional Fisheries Management Organization (RFMO) and are only available to the local fleet of Taiwan. Thus, using AIS of the possible FOC contacts from the Global Fishing Watch data, a matching algorithm can be run to identify possible transshipment activities. By law, the local vessels have to submit a report to the authorities of their transshipment activity. Failing to do so can be an indicator of the vessel being engaged in IUU transshipment[10].

4. CONCLUSION

Illegal, Unreported, and Unregulated fishing is a major challenge that affects a huge part of the world. It has major implications for the lives of the local fishermen and the local food supply as fisheries support 3 billion people all around the world. Tracking and monitoring all the ships and vessels roaming around the oceans is a monumental task as the oceans cover 70% of the Earth's surface area. Organisations like the Global Fishing Watch release AIS data to the general public for free, so that vessels can be tracked by anyone anywhere as long as they have an internet connection. As AIS transceivers generate a lot of data at frequent intervals it becomes necessary to use machine learning and deep learning algorithms to process such a large amount of data. VMS data gives a clearer picture in terms of understanding the movement of vessels but it is not publicly available. Although there is a lack of expert labelled data in this domain various methods have been suggested by researchers to detect fishing activity using AIS or VMS data. Leveraging new technologies like deep learning and neural networks are going to be paramount in detecting fishing activity due to the vastness of the data.

5. FUTURE WORK

The detection of fishing activity can be made more resilient with improvement in the quality and reliability of the sensors which transmit the data. It can be improved if the detection is based on the maritime zonal requirements as agreed upon in international treaties. Having access to more expert-labeled data from fisheries around the world would help a lot in improving the accuracy of the project. Publicly available VMS data can allow researchers to explore this domain with more ease as VMS data paints a more complete and detailed picture of vessel activity. AIS, alone, isn't a very good tool to predict the suspicious behavior of a vessel, thus a more robust signaling system for vessels that can't be switched off easily might be required to help in the detection of IUU activity.

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