TransNav
http://www.transnav.eu
the International Journal on Marine Navigation and Safety of Sea Transportation
Volume 14
Number 3
September 2020
DOI: 10.12716/1001.14.03.01

# A Study of Correlation between Fishing Activity and AIS Data by Deep Learning

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ABSTRACT: Previous researches on the prediction of fishing activities mainly rely on the speed over ground (SOG) as the referential attribute to determine whether the vessel is navigating or in fishing operation. Since more and more fishing vessels install Automatic Identification System (AIS) either voluntarily or under regulatory requirement, data collected from AIS in real time provide more attributes than SOG which may be utilized to improve the prediction. To be specific, the ships' trajectory patterns and the changes in course become available and should be considered.
This paper aims to improve the accuracy in the identification of fishing activities. First, we do feature extraction from the AIS data of coastal waters around Taiwan and build a Recurrent Neural Network (RNN) model. Then, the activity data of fishing vessels are divided into fishing and non-fishing. Finally, based on the testing by feeding various fishing activity data, we can identify the fishing status automatically.

## 1 INTRODUCTION

Ever since the 1982 United Nations Convention on the Law of the Sea (UNCLOS) entered into force in 1994, the rights and duties of coastal, port and flag States in respect of principal maritime zones, namely the territorial sea, the exclusive economic zone (EEZ) and the high seas became the bases and driving forces for the rapid changes in the maritime management. Systems or schemes have been introduced to enhance the safety of life at sea, the environment protection, and maritime security.

As for the fisheries, besides the provisions of UNCLOS, the rapid depletion of key fish stocks has made it imperative that governments achieve greater control over fishing activities. In order to ensure sustainable fisheries, a mechanism called monitoring, control and surveillance (MCS) was introduced for implementation of agreed policies, plans or strategies for oceans and fisheries management [1].

Fisheries MCS can be defined as follows:

- “Monitoring” includes the collection, measurement and analysis of fishing activities including, but not limited to: catch, species composition, fishing effort, by-catch, discards, area of operations, etc.
- “Control” involves the specification of the terms and conditions under which resources can be harvested.
- “Surveillance” involves the regulation and supervision of fishing activity to ensure the national legislation and terms, conditions of access, and management measures are observed.

Flag States have the responsibility to know where their vessels are located. Flag States must also have some means of determining what each of their fishing vessels is catching. Although the data to be reported will vary from fishery to fishery, flag States should require their fishing vessels to report timely, complete and accurate information concerning fishery activities, including: vessel identification, position, course, speed, fishing effort, catch composition, zone entry/exit (including closed areas entry/exit). Flag States should also establish a mechanism to verify the accuracy of reported data and should penalize the failure to report and misreporting of data. For serious offences, such sanctions should include withdrawal or suspension of the vessel's authorization to fish.

The term "illegal, unreported and unregulated fishing" or IUU fishing is used to describe a wide range of irresponsible fishing activities, such as reflagging of fishing vessels to evade controls, fishing in areas without authorization, failure to report or misreporting catches. Such activities undermine efforts to manage marine fisheries properly and impedes progress toward the goal of sustainable fisheries.

Apparently, automatic detection and identification of fishing activities is essential to effective fishery MCS and sustainable fishery. This is the focus and main purpose of the work presented in this paper. It is envisioned that development of such functionality can further contribute to maritime spatial planning as well as maritime safety and security.

One of the most efficient and cost-effective tool for fisheries MCS is Vessel Monitoring System (VMS). Over the past 20 years, a growing number of States have introduced VMS requirements for their fishing vessels or as a condition of access for foreign vessels to fish in waters under their jurisdiction. Most international agreements adopted by regional fisheries management organizations (RFMOs) also require VMS.

In the early days of fishing activity detection, most researchers use data collected by VMS to predict when the vessels is in fishing operation. VMS mainly relies on satellite-based automatic location communicators, including Inmarsat-C, ARGOS, and Iridium, and the position report interval is usually set at 1 hour for coastal monitoring due to the cost.

The vessel's speed is used as a threshold to judge the behavior [2,3,4]. However only the trawling accuracy is relatively high when compared with other fishing methods. In order to improve the accuracy, Artificial neural networks(ANN) are used for analyzing the VMS data, and the optimization of the parameters is adjusted by sensitivity method [5,6]. Compared with VMS, Automatic Identification System (AIS) provides much detailed locations and more attributes of the vessels in real-time. Besides, AIS position reports are broadcast in maritime VHF band using standard unencrypted message formats, which can be collected by coastal receivers in range. AIS data can even be received by satellites, thus called Satellite AIS (S-AIS). S-AIS can cover deep sea fishing area, although with some data loss and latency. AIS data has become an important asset to researches on vessel tracks and fishing behaviors, e.g. [7]. In [8], machine learning is used to identify the three type of fishing activity, i.e. trawler, longliner, and purse seiner, from S-AIS data and label the points as fishing or non-fishing. Because longline fishing is a complicated fishing method, in [9] a novel approach is proposed for identifying fishing activity using the Conditional Random Fields. In [10], deep learning is used with auto-encoders to automatically find fishing features. However, the research in [10] is using S-AIS data to detect fishing activity of distant water fishing. So far in the literature, to the author's knowledge, none of the AIS-based fishing activity detection is for small and medium-sized fishing vessels on coastal waters.

To detect fishing activity and improve identification performance, we implement an identification methodology based on deep learning. Key features of fishing are created in advance and a multi-layered bidirectional long short term memory model is built to predict three types of fishing activities, namely trawling, trolling, and longline fishing, on coastal waters around Taiwan. This paper is organized as follows. Section II introduces terminologies used throughout this paper. Section III describes the data preprocessing and reports the results of the experiments. Conclusions are then presented in Section IV.

## 2 BACKGROUND OF METHODS

### 2.1 *Recurrent Neural Network*

Recurrent Neural Network (RNN) is a well-known model to deal with sequential data. The structure of a simple RNN, illustrated in Fig. 1, has feedback loops which let model maintain memory over time. This means input has not only the result of the previous hidden layer, but also the value predicted at the previous time.

An RNN can be described mathematically as follows. Given a sequence of feature vector $X_T$ = $\{x_1, x_2, \dots, x_T\}$. An RNN with a hidden vector sequence $H_T = \{h_1, h_2, \dots, h_T\}$ and output vector sequence $Y_T = \{y_1, y_2, \dots, y_T\}$ is calculated as follows:

$$h_t = \sigma_h\left(W_1 x_t + W_h h_{t-1} + b_1\right) \tag{1}$$

$$y_t = \sigma_y\left(W_2 h_t + b_2\right) \tag{2}$$

where $W_i$ and $b_i$ denote the input weight matrix and bias vector, respectively. $W_h$ denotes the weight matrix between consecutive hidden states ($h_{t-1}$ and $h_t$), while $\sigma_h$ and $\sigma_y$ denote activation functions of the hidden layer and output layer.

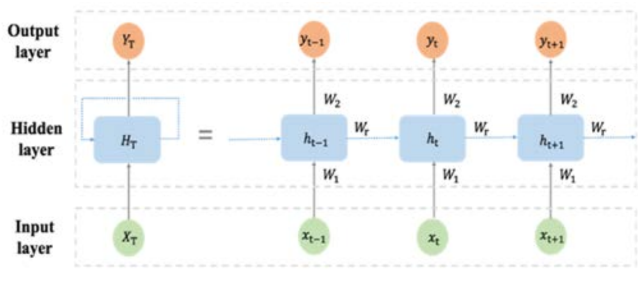



Figure 1. Recurrent Neural Network architecture

### 2.2 *Bidirectional Recurrent Neural Network*

A bidirectional RNN (BRNN), illustrated in Fig. 2, consists of two separate hidden layers that both connect to the same input and output. The first layer learns from the previous time steps and the second layer learns from the following time steps. Therefore, BRNN can exploit information both from the past and the future.

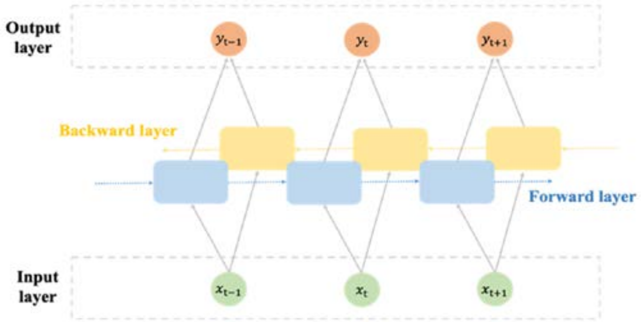



Figure 2. Bidirectional recurrent neural network architecture

### 2.3 *Long Short-Term Memory*

When the sequence is long enough, RNNs suffer from the vanishing gradient problem. Therefore, RNN is able to remember only short-term memory sequences. To solve this problem, a variant of RNN called Long Short-Term Memory (LSTM) was proposed by Hochreiter & Schmidhuber[11]. The only different component between LSTM architecture and RNN architecture is the memory cell. As illustrated in Fig. 3, there are three gates in an LSTM cell, including an input gate, a forget gate, and an output gate, denoted as $i_t$, $f_t$ and $o_t$ respectively. Each gate has a value between 0 and 1. The value 0 means that the gate is closed, while the value 1 means that the gate is opened. In an LSTM layer, the hidden layer output $h_t$ in Eq.1 is replaced by the following equations:

$$i_t = \sigma\left(W_x^i x_t + W_h^i h_{t-1} + b_1\right) \tag{3}$$

$$f_t = \sigma\left(W_x^f x_t + W_h^f h_{t-1} + b_2\right) \tag{4}$$

$$c_t = f_t c_{t-1} + i_t tanh\left(W_x^c x_t + W_h^c h_{t-1} + b_3\right) \tag{5}$$

$$o_t = \sigma\left(W_x^o x_t + W_h^o h_{t-1} + b_4\right) \tag{6}$$

$$h_t = o_t \tanh\left(c_t\right) \tag{7}$$

where $c_t$ is the memory cell, superscripts i, f, o, c are the input gate, forget gate, output gate and input cell state, respectively.

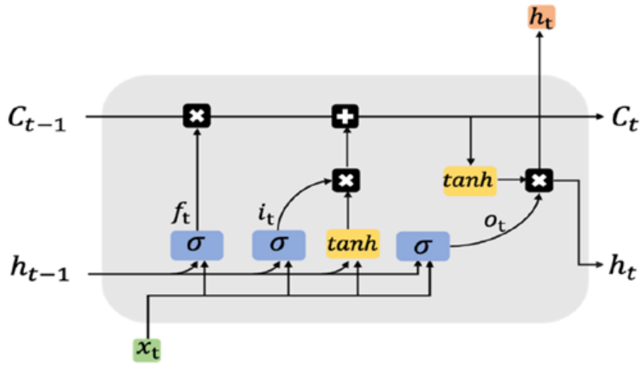



Figure 3. Long shor-term memory cell

## 3 EXPERIMENTS AND RESULTS

### 3.1 *Data Pre-processing*

- Data Cleaning: In this experiment, we use AIS data of class B shipborne stations and sort the data in order according to Maritime Mobile Service Identity (MMSI) and timestamps. AIS data are subject to the integrity, availability and accuracy of inputs from interfaced shipborne sensors as well as configuration settings and manual entries [12]. Hence data pre-processing needs to be performed, e.g. to remove repetitive data points or duplicate MMSIs and outliers.
- Feature Selection: The following three features are not considered suitable for use:
- Ship Size or Tonnage: It affects the speed of fishing. Tonnage may be obtained separately from VMS database or inferred indirectly from the ship length reported in AIS data. However, in coastal waters around Taiwan, the ship length information in AIS data of fishing vessels are either unavailable or unreliable.
- Heading: Almost all coastal Taiwanese fishing vessels do not have gyrocompass installed and connected to AIS, thus the heading attribute is basically unavailable.
- Latitude and Longitude: Using absolute latitude and longitude values of the positions leads to overfitting, which may make the prediction accurate only in that specific area. It is more appropriate to use the calculated relative positions between consecutive points.

Since fishing activity is highly correlated with the ship's speed and the change of ship's course, the Speed over Ground (SOG) and change in Course over Ground (COG) are indispensable features. According to our observation, the characteristics in operation distance and operation time differ in each type of fishing method. SOG is the instantaneous speed, which may cause some errors when used in judging long-term behavior. In order to improve fishing activity detection, we not only consider the SOG and change of COG, but also calculate the differential time ($\Delta T$), relative distance ($\Delta D$) and average speed ($V_{avg}$) between consecutive points, as shown in Fig.4.

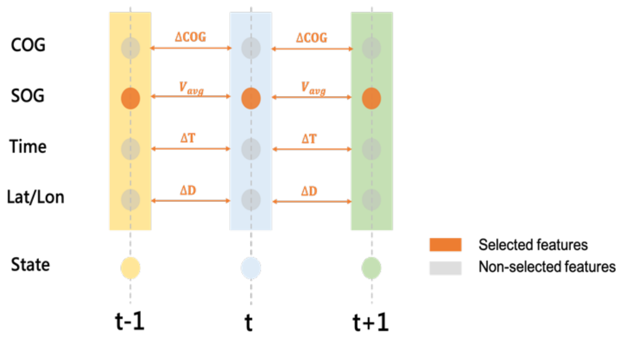



Figure 4. Feature selection

## 3.2 *Results*

In this study, we build the multi-layer bidirectional LSTM model with Keras, train three models by three types of fishing activities and design three experiments to compare the effect of feature selection. Case 1 use one feature: SOG. Case 2 use three features: SOG, $\Delta$COG and $V_{avg}$. Case 3 use five features: SOG, $\Delta$COG, $V_{avg}$, $\Delta T$ and $\Delta$D. The results are shown in TABLE I.

Table 1. Evaluation Using Different Features

| Fishing Gear Type | Feature Selection Case 1. | Case 2. | Case 3. | Source Data Track Size | % of Fishing Activity |
|---|---|---|---|---|---|
| Trawling | 85.7% | 95.9% | 94.4% | 3389258.91% | |
| Longlining | 72.3% | 86.4% | 89.8% | 3939363.15% | |
| Trolling | 91.3% | 99.1% | 99.6% | 8474086.71% | |

TABLE I shows that considering only SOG is not enough for the detection of trawling. Best performance for trawling detection is obtained using SOG, $\Delta$COG and $V_{avg}$. The longlining, as a complicated fishing activity, is easily affected by the depth of the longline setting. If the detection only considers SOG, the accuracy is not good. After adding $\Delta$COG and $V_{avg}$, the prediction accuracy is raised by 14.1%. By further adding $\Delta$T and $\Delta$D, the accuracy is raised by another 3.5%. The accuracy of trolling is already rather good when only SOG is considered. When SOG, $\Delta$COG, $V_{avg}$, $\Delta T$ and $\Delta$D are considered, the accuracy can be as high as 99.6%.

In general, Case 3 have better performance. Fig. 5, Fig. 6 and Fig. 7 show the visualization of three predicted results of Case 3 for different types of fishing. Green point represents that it is actually fishing and predicted to be fishing. Red point represents that it is actually non-fishing and predicted to be non-fishing. Blue point represents that it is actually fishing but is predicted to be non-fishing. Yellow point represents that it is actually non-fishing but is predicted to be fishing.

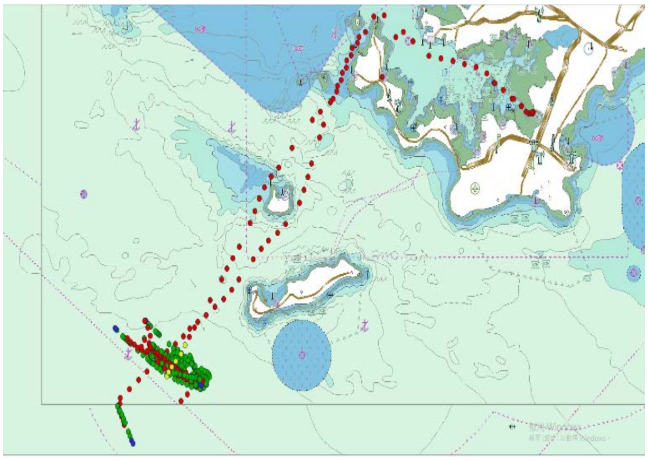


Figure 5. The visualization of trawling detection results

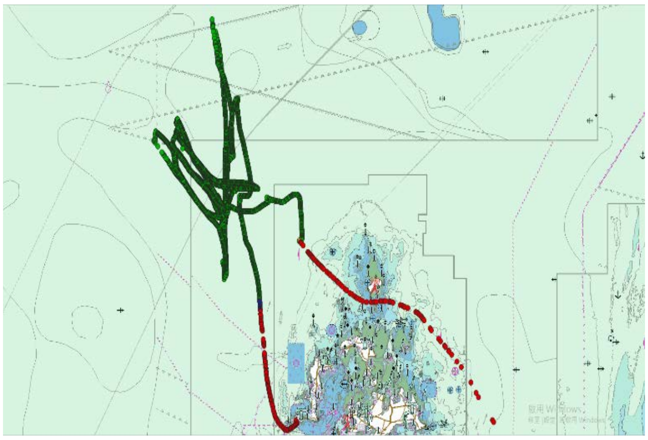


Figure 6. The visualization of trolling detection results

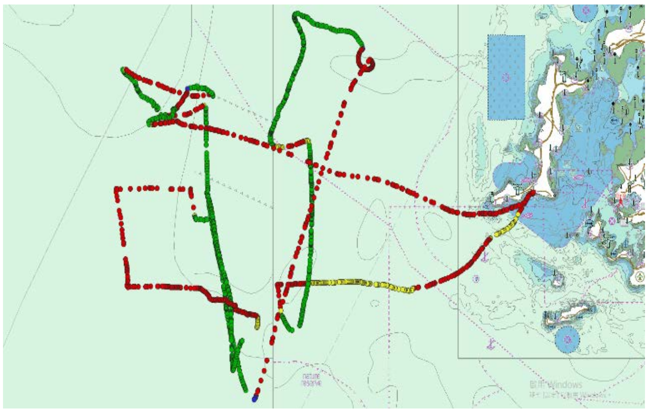
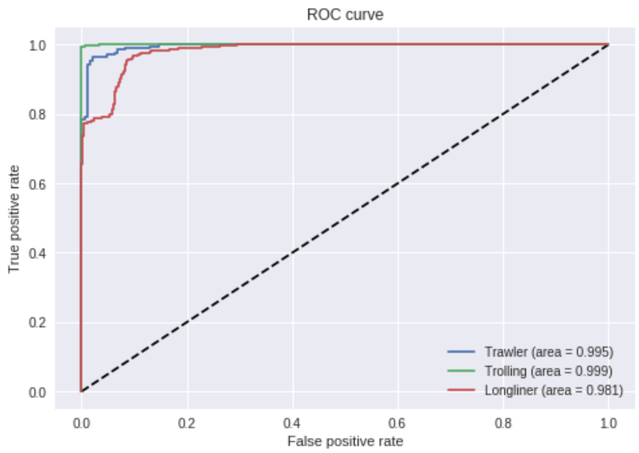


Figure 7. The visualization of longlining detection results

Table 2. Detailed Performance Assessment of Case 3

| Fishing Gear Type | Assessment of prediction Accuracy | Sensitivity | Specificity | Positive Predictive Value(PPV) | Negative Predictive Value(NPV) | F1 score | AUC |
|---|---|---|---|---|---|---|---|
| Trawling | 0.944 | 0.990 | 0.469 | 0.907 | 0.989 | 0.947 | 0.995 |
| Longlining | 0.898 | 0.840 | 0.442 | 0.988 | 0.806 | 0.908 | 0.981 |
| Trolling | 0.996 | 0.999 | 0.037 | 0.997 | 0.989 | 0.998 | 0.999 |

Detailed performance assessment of Case 3 are shown in TABLE II. In order not to be affected by the threshold, we use ROC curve (receiver operating characteristic curve) and AUC (Area under the ROC Curve) to assess the performance of the model, as illustrates in Fig.8. The AUC values of three fishing activity model are all exceeding 0.9, thus outstanding discriminations are obtained.




Fgure 8. The ROC curve of Case 3.

## 4 CONCLUSIONS

This paper presents an approach to detect fishing activities using multi-layered bidirectional LSTM model for three main fishing types on the coastal waters around Taiwan. Key features from AIS data are found to raise the accuracy and verify their influence on three models. For further research to enhance the performance in fishing activity detection, hybrid RNN model might be used to learn better spatial representation and include auxiliary information such as weather conditions or current data.

## ACKNOWLEDGMENT

Authors thank the Maritime and Port Bureau, Ministry of Transportation and Communications for providing access to the AIS data.

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