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Identification of Vessel Class with LSTM using Kinematic Features in Maritime Traffic Control

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Abstract—Prevent abuse and illegal activities in a given area of the sea is a very difficult and expensive task. Artificial intelligence offers the possibility to implement new methods to identify the vessel class type from the kinematic features of the vessel itself. The task strictly depends on the quality of the data. This paper explores the application of a deep Long Short-Term Memory model by using AIS flow only with a relatively low quality. The proposed model reaches high accuracy on detecting nine vessel classes representing the most common vessel types in the Ionian-Adriatic Sea. The model has been applied during the Adriatic-Ionian trial period of the international EU ANDROMEDA H2020 project to identify vessels performing behaviours far from the expected one, depending on the declared type.

Keywords—Maritime Surveillance, Artificial Intelligence, Behaviour Analysis, LSTM.

I. Introduction

Achieving situational awareness in the maritime environment requires persistent and developing surveillance techniques. Border security consists of discovering illegal activities such as illegal fishing, smuggling, and human trafficking. National maritime authorities have the responsibility to control and prevent illicit, but there are lots of limitations due to lack of information, the presence of non-cooperative entities in a given area, and so on. This work is part of the Andromeda Horizon2020 project, titled 'An Enhanced Common Information Sharing Environment for Border Command, Control and Coordination Systems'. In the frame of this project, the present work focuses on predicting vessel class types from the kinematic profile, providing a useful model to detect vessels that are performing illegal activities (i.e. fishing into a forbidden area) or more generally, vessels performing abnormal kinematic patterns. In the literature, it isn't rare to see methods that are specialized in single class activities, in particular the classification of fishing vessels [1]. For a single class, binary classification point-based time series have proved to be very effective yet with a relatively denser feature space [2]. Most of the current methods rely on the availability of high-quality data from multiple sources. Predicting the ship class type only from the AIS stream is a hard challenge: the transmitted data is always prone to error either because of sensor imperfection or natural factors such as wind, currents, and ocean floor (seafloor) relief.

Although, a relatively good vessel motion classification is achievable with LSTMs, transforming such a model into type classification isn't straightforward [3] because of the high number of different vessel types and their different manoeuvrability constraints.

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II. Data Processing

The AIS is a vessel tracking system that uses transceivers on ships sending information about it and is the primary method of collision avoidance for water transport. The AIS receiver reports *ASCII* data packets as a byte stream using the *NMEA* 0.183 standards. The AIS data consists of three main data categories: static, dynamic, and voyage-related data. In this study, we used the following information:

- Static: *MMSI*[1], *Ship Type and Vessel Name*[2]
- Dynamic positional: Longitude, Latitude

Using only positional data (longitude, latitude) for positional analysis is very challenging. When a vessel is stationary, the natural effects such as wind and currents force the vessel to move back and forth in a small area, and this error coupled with the sensory errors create noise in the transmitted data. Such factors affect the data even when the vessel is on the move, to a degree that the transmission of the linear path appears to be curved with many small bearing changes. Furthermore, some of the vessels either move very slowly or are *adrift*[3] for too long, as a result, such vessels appear to have travelled much longer distances.

In order to overcome uncertainties mentioned above, we propose the implementation of the following kinematic profile. For each vessel v in the bounding box, let $trj_v(t) = \{(long_\tau, lat_\tau), \tau \in [t-T, t]\}$ the sequence of reported latitude and longitude in the time T. Let define as I the uniform partition of the interval $[0, T]$ into N parts. Let ψ the function that refer points in trajectory to regular time steps using linear interpolation and $\xi_v(t) = \psi(trj_v(t))$. Finally, let $X = \{\xi_v(t), v \in V, t\}$ the set of all segments of trajectories of length T for each vessel v. Three main parameters have been taken into account:

- λ (expressed in meters): it is the length of the edge of the square containing all the points in a single trajectory pattern
- θ (expressed in meters): the minimum travelled distance between consecutive time steps for the vessel
- σ (real number between 0 and 1): the ratio between the number of intervals within travelled distance lower than θ over $N-1$

A trajectory pattern is valid if all of the following conditions are satisfied simultaneously:

$$d_{geodetic}((\min \xi_v(t)^{long}, \min \xi_v(t)^{lat}), (\max \xi_v(t)^{long}, \max \xi_v(t)^{lat})) > \lambda \tag{1}$$

[1]probability of spoofing over MMSI information in small areas is very low
[2]this information are inherently used in the application but not in the model.
[3](of a boat or its passengers) floating without being either moored or steered.

$$\frac{\|\{i : d_{geodetic}(\xi_i, \xi_{i+1}) < \theta\}\|}{N-1} < \sigma \tag{2}$$

Normalized kinematic profile of the trajectory is defined as a vector $f \in R^{3\cdot(N-2)}$ where:

$$\begin{aligned} f_{0i} =& \frac{\|v_i\|}{\max(\|v_i\|)} \\ f_{1i} =& \frac{\|a_i\|}{\max(\|a_i\|)} \\ f_{2i} =& \frac{1}{2}\left(1 + \frac{v_i \cdot v_{i+1}}{\|v_i\|\|v_{i+1}\|}\right) \end{aligned} \tag{3}$$

where v_i, a_i are the speed and acceleration vectors respectively.

III. Method

Long Short-Term Memory (LSTM)[4] is a recurrent neural network (RNN) architecture, designed to model temporal sequences and their long-range dependencies. The LSTM contains memory blocks in the recurrent hidden layer, containing memory cells with self-connections storing the temporal state of the network and gates to control the flow of information. Each block has an input gate, controlling the flow of input activations, and an output gate controlling the output flow into the rest of the network. In LSTM network computes a mapping from an input sequence $x = (x_1, \ldots, x_T)$ to an output sequence $y = (y_1, \ldots, y_T)$ by calculating the network unit activations using the following equations iteratively from $t = 1$ to T:

$$\begin{aligned} i_t =& \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \\ f_t =& \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f) \\ c_t =& f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \\ o_t =& \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \\ m_t =& o_t \odot h(c_t) \\ y_t =& \varphi(W_{ym}m_t + b_y) \end{aligned} \tag{4}$$

where the W terms are the weights, the b terms denote bias, σ is the sigmoid, and i, f, o and c are respectively the input gate, forget gate, output gate and cell activation vectors; g and h are respectively the activation functions of the cell input and output, in this paper $tanh$, and φ is the output activation function. Deep LSTM RNNs are obtained by stacking more LSTM layers. By using deep layers, the network learns at different timescales[5].

IV. Experimental Results

Data are related to the area identified by the bounding box B identified by the points $(35N,\ 11E)$, $(46N,\ 25E)$ and to the period from 20^{th} October 2019 to 27^{th} May 2020. Lack of contiguity affects data for the declared period. The parameter T has been set to $9000s$. This time comes from heuristic considerations about the modification of vessel features over the trajectory. The parameter N has been set to 50, which is equivalent to consider trajectory update every $180s$. Indeed, a lower threshold does not reflect sensitive changes because, in general, vessel speed is low; a bigger value makes features less accurate. Vessel types have been grouped in classes as shown in I. Classes have been defined to have homogeneous kinematic limits between class members.

TABLE I
Table of vessel classes and ship type.

Class Name	Class Id	NMEA ship type
WingInGrnd	1	[20-28]
SAR	2	[29, 51]
Fishing	3	[30]
Tug	4	[31-32, 52]
SpecialCraft	5	[33-35, 50, 53-59]
Sailing Vessel	6	[36]
PleasureCraft	7	[37]
High-SpeedCraft	8	[40-49]
Passenger	9	[60-69]
CargoS	10	[70]
Cargo	11	[71-79]
TankerS	12	[80]
Tanker	13	[81-84, 85-89]

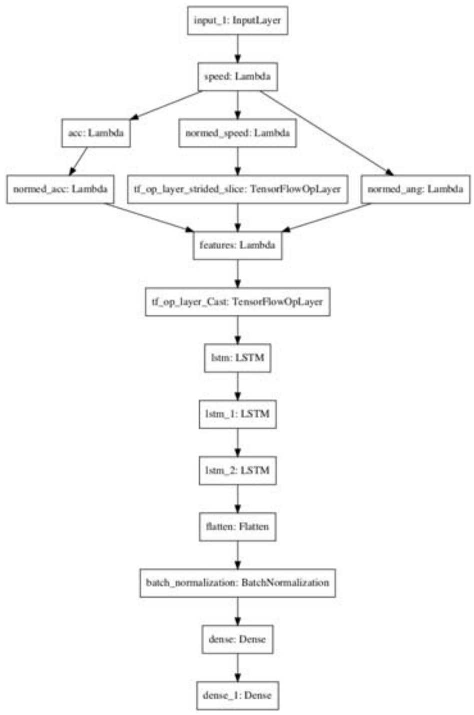

Fig. 1. LSTM Model structure

The model has been defined as follows:

Figure 1 shows the graph of the model defined in Tensorflow [6] which contains the computations and the data that flow between operations. The initial part of the graph makes the normalized kinematic profile starting on the trajectory as described in the previous section. Then, the core section of the model is three stacked LSTM layers. After the Flatten layer, there is batch normalization for speeding up the training process and also as a regularization technique. Thereafter, the model finishes with a sequence of two dense layers, fully connected. The last layer returns an array with each element

contains a score that indicates the current vessel which belongs to one of the classes. Moreover, we use sparse categorical cross-entropy for the loss function, and for each layer, the activation function is set to ReLU except the last layer that uses the Softmax function.
The accuracy of the model is reported below:

TABLE II
HYPER PARAMETERS VS MODEL ACCURACY.

optimal parameters	$\lambda = 0$, $\theta = 0$, $\sigma = 0$	$\lambda = 0$, $\theta = 0$, $\sigma = 0.4$
0.92	0.68	0.85

Table II shows the sensibility of the model with respect to the hyperparameters. The result is coherent with a simple intuition, i.e., it is impossible to guess the vessel class for 'static' and 'almost static' vessels.

The figures 2 show the confusion matrix of the models with the parameters reported in the above table. The matrix shows for each class the number of predicted and actual instances. The last row and the last column represent the precision and recall (or sensitivity) for each vessel class, positive and negative rates are marked with green and red colours respectively.

One can easily deduce the inter-class relationships between vessel class types "Cargo" and "CargoS" and "Tanker" and "TankerS" from each confusion matrix, as these vessel class types have similar characteristics. It's interesting to see that the fishing vessel class type maintains high accuracy in each kinematic profile. This can be considered as additional proof for the validity of kinematic profiles, since the fishing vessels have very distinguishable trajectory patterns.

V. Conclusion

The work proved how an LSTM model can be used to detect anomalies in maritime traffic and, in particular, to discover vessel activities. The proposed approach applies to the case of illegal fishing by detecting vessel behaviours in a restricted area. Furthermore, it could be applied directly to radar data. One important aspect that will be analysed is the geometrical approach to the set of all behaviours in a given area when time varies. In particular, looking at the behaviours' space as a point cloud is possible to calculate the topological features. By comparing the features and their evolution over time, it is possible to disclose the underlying relation between patterns, intrinsic structure set, seasonality, and hidden cooperation activities.

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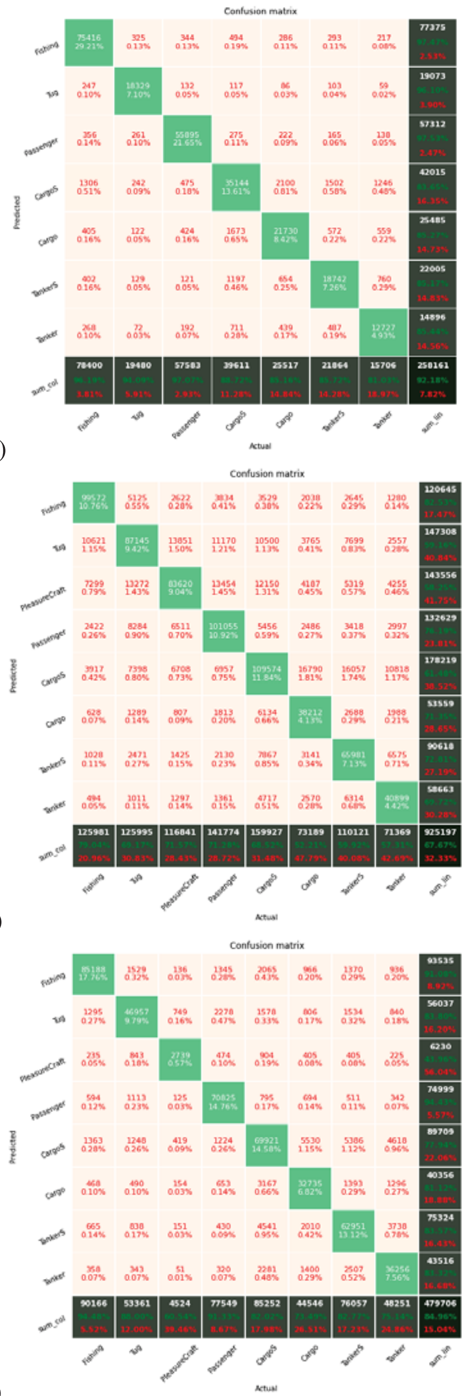

(a) (b) (c)

Fig. 2. (a) Confusion Matrix with optimal hyperparameters (b) Confusion Matrix with hyperparameters set to zero (c) Confusion Matrix with improved $\lambda = 0$, $\theta = 0$, $\sigma = 0.4$

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