Deep learning to enhance maritime situation awareness

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Abstract: *Maritime surveillance sensors like AIS (Automatic Identification System) and Radar provide useful information for decision-making support, which is of paramount importance for effective operations against maritime threats and illegal activities [1]. However, decision-making systems that trust solely on AIS information tend to fail in real situations because such information could be missing, inaccurate or even deceptive [2]. On the other hand, only Radar information is not enough to get a complete description of the maritime situational picture. This paper proposes a deep learning framework for vessel monitoring that examines a particular scenario where a deep learning solution can infer a navigation status based on the vessels trajectories, and thus to detect suspicious vessels activities. For this purpose, a dataset, named DeepMarine, has been specifically created by collecting data of AIS historical recordings. We demonstrate the performance of the developed deep learning framework for the proposed vessels activity classification, which can be ultimately used to report illegal activities.*

1. Introduction

Airbus Defense and Space (ADS) has developed Airborne Mission Systems since more than twenty years ago. Its Fully Integrated Tactical System (FITS) based on a suite of different sensors is currently operating in more than fifty aircrafts like C-212, CN-235, C-295 and P-3. One of the FITS applications is for the maritime domain. Two main sources of information from the FITS are AIS and X-band radar. Broadcasted AIS messages contain kinematic and static data that can be transformed into useful information. Some of the fields included in the AIS messages are vessels identity, navigation status, rate of turn, speed over ground, position, course over ground or true heading. However, it is only mandatory for larger vessels, and therefore maritime radar data is still essential for smaller and non-cooperative vessels. AIS available data is used for training purposes as this kind of information is labeled, but in an operational environment, this information is not always available and only radar information can be used. In those cases information about the position and the velocity of the vessels are used to infer what the vessels are doing.

An automatic capability for early detection of illegal activities can help human operators to improve the probability of detection of such activities. Nowadays, this is usually done by highly skilled operators that constantly monitor and analyze information of a large area containing hundreds of vessels. Moreover, the “modus operandi” of these activities is in constant evolution due to the criminals’ purpose of deceiving the authorities. Subsequently, a high capability to adapt to changing behavioral patterns is required. This is the reason why a solution based on the use of a Neural Network (NN) algorithm is proposed as it is able to be adapted to different scenarios and it is able to manage a big amount of data which is available as AIS information can be obtained for a long time period.

In some cases, the operator knows exactly what situations to look for, and it is then possible to define a set of rules for them [3-5]. For instance, the system in [5] can identify a number of basic spatial and kinematical relations among objects, and then deduce different situations, e.g. smuggling, hijacking and piloting.

In other cases, the operator looks for situations that deviate from the considered normal behavior in an unspecified manner (i.e. anomaly detection). This insight is more complex to automatize, nonetheless there have been different approaches in the literature that address the anomaly detection problem in maritime surveillance applications. Data-Driven algorithms [6] build a model of normal vessel behavior from historical motion data. The models are then used to classify new vessel observations as normal or anomalous. They generally estimate the degree of deviation of new target trajectories from the learned model of normal trajectories. Different algorithms are capable of detecting different types of anomaly (e.g. point or speed anomalies) [7]. In [8], anomaly detection algorithms are divided into two classes based on the models' learning characteristics: Geographical (map-dependent) model-based methods and parametrical (map-independent) model-based methods. These last ones have been well-studied, especially those that make use of trajectory and dynamic information. Features of vessel motion are analyzed over time by considering trajectories [9]. Most of them perform a clustering strategy to divide the trajectories into different groups. By clustering similar trajectories corresponding to regular traffic, a model of normal vessel routes can be constructed [10] [11]. They typically assume that in specific areas the vessels tend to have similar behaviors, which are subject to be clustered using different algorithms (kmeans, DBSCAN, etc.). Some of them classify a trajectory as anomalous based on the distance to the closest set of trajectories, technique called k-nearest neighbors [12] [13]. When the distance among trajectories is expressed in terms of likelihood, a probabilistic anomaly detection can be inferred [14] [15]. On the other hand, some methods perform a pre-processing of the trajectories, since commonly used similarity measures, such as the Euclidean distance, require equally spaced and properly aligned trajectories. In [16], unlike previous references, each cluster is a speed mode.

However, clustering steps could result in loss of information. Moreover, the detection of anomalies needs to be performed on-line in surveillance applications. In this context, it is crucial to reduce delays between the start of the anomalous behavior and the alarm raised by the monitoring system. Sequential process control techniques have been proposed to shorten the average time required to signal a change in the normal process [17] [18]. It should be remarked that these sequential techniques assume the data streams are regularly-sampled, but this is not true in real applications, and interpolation or motion estimation methods should be additionally used.

Statistical [19] and machine learning based techniques [20] have been also proposed for anomaly activity detection, where most of the approaches are based on unsupervised learning. In [21], a Trajectory Cluster Modelling (TCM) is proposed, representing one of the first attempts to apply machine learning to anomaly detection in the maritime domain. However, the development of learning-based systems is a critical challenge because of the noise, irregular time-sampling, and huge amount of data. For this reason, the presented paper proposes a supervised deep learning solution to infer deep semantics and behavior from the vessels' trajectories a basis for illegal activity detection. For this purpose, a specific NN has been designed, which has two independent branches that process two independent input streams of Speed Over Ground (SOG) and Course Over Ground (COG) data. The outputs of these branches are concatenated and process by a fully-connected subnetwork, whose output is a predicted label that contains the navigation status: stationary, cruising, and fishing. This information could be also very useful for target classification and identification task in a multi-sensor engine.

2. Deep Learning Framework

A convolutional neural network (CNN) has been designed to infer the navigation status from the AIS information. Then, both AIS and Radar trajectories, can be used to detect different vessel behaviors. For example, a fishing activity could be recognized by observing joint variations of course and speed, and then an alert could be raised in case of fishing in not-allowable areas. Note that both positional data and ship information (e.g. navigation status, ship type, or ship name) are necessary for the detection of an anomaly.

The CNN has two independent inputs: a stream with SOG data and another stream with COG information, both ones extracted from the AIS historical recordings. The input data streams are vectors with a fixed number of samples, which are normalized to deal with the different nature of information and their range of values. It is assumed that this information is enough discriminative to allow the CNN to infer correctly the navigation status. In the case of a fishing trajectory, the high frequency changes of SOG values are very discriminative. The output of the CNN is a label that contains the navigation status: stationary, cruising, and fishing.

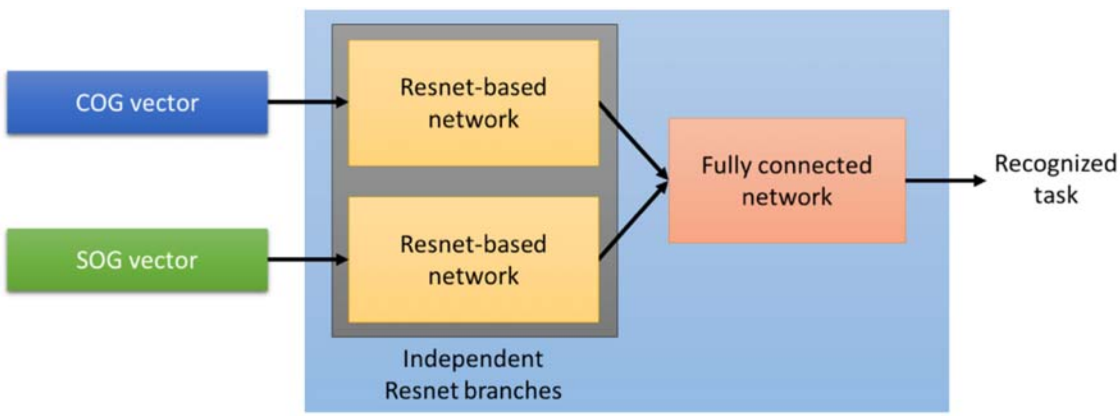

Figure 1 Deep learning based solution

The architecture of the CNN is shown in Figure 1, and it is composed by two independent branches and a fully-connected sub-network. The two independent branches process independently every input vector (COG and SOG) and have been designed using a Residual Network architecture [24], also called ResNet, which improves the convergence speed. Thus, every branch is composed by 28 layers divided into 10 blocks, as shown in Figure 2. Every block contains a 1D convolutional layer, a batch normalization layer, and an activation layer. The 1D convolutional layer have 32 filters of size 3x1. A ResNet shortcut is added between every two blocks of layers. This shortcut is a simple sum operation when the input and output are of the same dimensions, and it is a projection shortcut when the dimensions are different.

The outputs of both ResNet branches are merged and processed by a fully-connected sub-network that makes the final prediction about the navigation status by integrating the information processed by every ResNet branch. The fully-connected sub-network is composed of three dense layers. The first layer has 2048 elements, the second layer has 512 elements, and the last one is a softmax with three outputs, one for each considered navigation status.

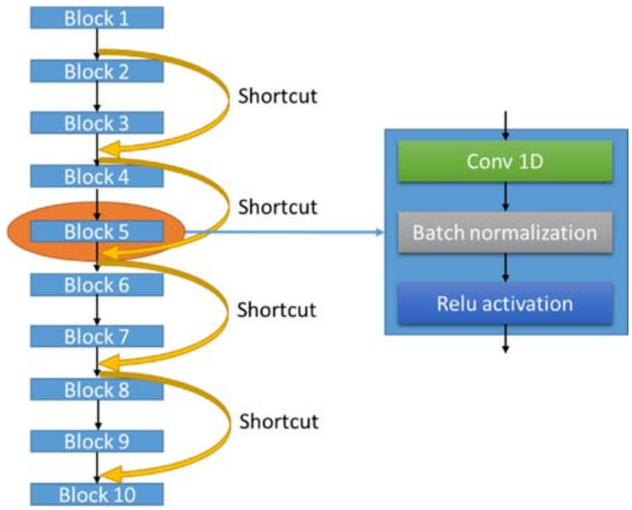

Figure 2 Resnet branch.

Regarding the training of the proposed CNN, the cross-entropy has been used as cost function and the Adam algorithm has been used as optimizer with a learning rate of 1e-4. Lastly, the batches are composed by 32 samples.

2. DeepMarine database

A database, named DeepMarine, is used as basis to classify different vessel behaviour. Taking into account the data quality (e.g. time resolution and completeness), AIS information is extracted from Marinecadastre (MarineC.), a free AIS data provider [25]. The MarineC data source contains historical records from 2009 to 2014 in USA. Records are temporally filtered, interpolated (1 minute) and stored in a monthly file by a Universal Transverse Mercator (UTM) zone. For the sake of privacy, the ship name and call sign fields are removed.

Recordings in a specific zone area per year could generate more than 70 GB of National Marine Electronics Association (NMEA) tracks coming from thousands of vessels. For the ongoing analysis, only a subset of AIS, namely position, speed, heading, maritime mobile service identity (MMSI), timestamp, and vessel-type, is needed. This information is complemented by external static sources of information like the vessel finder database [26].

As part of the database creation task, an automatic method for processing AIS information has been developed, able to handle a large amount of data. This method groups the raw AIS information into files, according to the vessels identify and year. Then, a first preprocessing is performed by removing small and noisy trajectories. Furthermore, trajectories whose samples length is smaller than a threshold are also discarded. Later, the trajectories (that can be quite long) are split into smaller chunks, with the purpose of detecting the navigation status in each one. It is assumed that the ship keeps its activity during several chunks, and every chunk contains the enough information to be able to infer the three considered navigation status: stationary, cruising, and fishing.

As the designed deep learning-based solution needs all the input trajectories to have the same length, i.e. the same number of samples, the entire trajectory has been split in blocks of the same temporal length, and an interpolation process have been made over them to have the same number of samples.

Samples of the database have been acquired in two different areas of the west coast of the United States of America (USA), so the database is composed by two sets of trajectories, one from the zone 15 and another one from the zone 17. Table 1 and Table 2 summarize the number of trajectory samples using different number of sampling points for each zone. The reason of considering different sampling rates is to analyze how the performance of the navigation status prediction changes with this parameter.

Table 1 Number of trajectories for zone 15.

Nº of sampling points	Stationary	Cruising	Fishing
100	14327	39107	20893
200	6472	18859	10429
300	3936	12204	6942

Table 2 Number of trajectories for zone 17.

Nº of sampling points	Stationary	Cruising	Fishing
100	4615	21251	7845
200	2151	10434	3912
300	1354	6864	2607

3. Results

The created database has been split into training (60% of the samples), validation (20% of the samples), and testing (20% of the samples) sets to properly train and test the proposed CNN. The metric used to measure the performance of the system is the precision that indicates the percentage of well classified samples of each class and can be expressed as follows:

$$Precision = 100 * \frac{true\ positive\ samples}{true\ positive\ samples + false\ positive\ samples},$$

where true positive samples represent the number of samples of each class classified as belonging to that class, and false positive samples represents the number of samples belonging to other classes classified as belonging to the selected class.

Table 3 and Table 4 show the precision results using the trajectories belonging to zone 15 and 17, respectively. It is important to notice that for all cases the precision value is greater than 50%, and that value increases when more samples are considered, i.e. more information has been used to predict the status.

Table 5 shows the precision results combining the samples belonging to zone 15 and zone 17, which indicate the capability of the solution to generalize using trajectories of different zones. In this case, the accuracy is somewhat lower for the Stationary and Cruising navigation status but it is higher for the Fishing one.

On overall, the total number of trajectories is quite scarce regarding the standards of deep learning, leading to a moderate system performance. But it is expected to highly increase the performance by creating a significantly larger database in the future. Nonetheless, these preliminary results prove the potential of applying a deep neural network for inferring information from trajectories.

Table 3 Accuracy results over the zone 15 of the DeepMarine database.

Nº of sampling points	Stationary	Cruising	Fishing
100	58 %	78 %	52 %
200	64 %	80 %	62 %
300	74 %	82 %	58 %

Table 4 Accuracy results over the zone 17 of the DeepMarine database.

Nº of sampling points	Stationary	Cruising	Fishing
100	72 %	87 %	68 %
200	70 %	88 %	66 %
300	78 %	89 %	69 %

Table 5 Accuracy results over the combination of zone 15 and zone 17 of the DeepMarine database.

Nº of sampling points	Stationary	Cruising	Fishing
100	51 %	63 %	78 %
200	55 %	66 %	83 %
300	61 %	70 %	88 %

4. Conclusions

This work has proposed a deep learning framework for vessel monitoring as a basis for anomaly detection, examining a scenario where the navigation status is inferred from vessels trajectories. We have demonstrated promising results classification problem by applying a supervised deep learning strategy. To this end, a dataset was created, however a greater amount of information should be collected in order to get more confidence and better results.

In addition, Radar flight recordings from AIRBUSS FITS system Flight Tests will be used as final test samples to validate the NN is able to infer the navigation status for non-collaborative targets on real environments.

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