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# PATTERN DETECTION IN MARITIME TRAFFIC FOR SAFETY ANALYSIS USING DEEP LEARNING

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## Abstract

The paper presents a novel approach for the detection of ship collision risks, by classifying images of ship traffic constructed from AIS data, using deep learning techniques. In this approach, the risk level of ship traffic patterns, according to maritime safety rules, is calculated, using a convolutional neural network trained on ship traffic image data. Experiments with the analysis of real ship traffic data from the English Channel are reported.

***Keywords:*** *AIS, COLREG, maritime safety, autonomous ships, computer vision, CNN, Deep Learning, Keras*

## 1. Problem statement

The capabilities of unmanned maritime vessels are rapidly improving, although the regulation and international laws that govern their operations are still in progress, Similar to land based autonomous vehicles, the autonomous path (route) planning of sea vessels is a fundamental capability. In contrast to ground and air autonomous path planning, however, route path planning present numerous challenges such as safety, complexity and environmental dynamics that hinder the development of reliable autonomous vessels [1]. Route planning algorithms for ships must comply with rules for safe distance, safe speed, angle of approach and many others. Ship collisions are rare events that may however, have a significant impact on the safety of people, ships, and other marine structures, as well as on the environment [2].

COLREGs is a set of safety regulations by the International Maritime Organisation (IMO) that describe potential collision scenarios for ships, such as crossing, head-on and overtaking, and suggests possible manoeuvres to avoid a collision. The 38 internationally agreed COLREG rules are compiled by the International Convention for Safety of Life at Sea and are known officially as the International Regulations for Preventing Collisions at Sea collision. However, although the rules provide a set of guidelines for safe manoeuvring at sea, they are aimed at human navigators, not unmanned systems. [3] Additionally, the subjective nature of COLREGs is one of the major causes of ship collisions. Indeed, it is estimated that human error contributes to between 89% and 96% of marine collisions (Rothblum, 2000 in [3]).

As ship technology is moving towards partial or full automation (i.e., autonomous ships), it is important for a ship's supervisory/guidance system to be able to detect unsafe sail situations, caused in particular, by the proximity and movement of other marine traffic. In this paper we propose that, with the use of machine learning techniques such as neural networks for machine vision, it is possible for the route planning system of the autonomous vessel to analyse images of maritime traffic and to detect potentially dangerous patterns, by classifying the ship traffic images according to their risk, following collision risk rules. Then, based on such information, the route planning system can plan a route that avoids the creation of collision risk situations, and in general, calculates a safe sailing route.

The paper is organised as follows. The next section describes the methodology we followed to obtain ship traffic data, and the data processing stages followed in order to use the data as inputs in a Convolutional Neural Network (CNN) for ship traffic pattern classification. Section 3 discusses the results we obtained, and their analysis in terms of metrics such as precision, recall, etc. Finally, Section 4 discusses strengths and limitations of our approach and plans for future research.

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## 2. Methods and Models

### 2.1 Computer vision in autonomous systems

In recent years, deep machine learning-based visual perception has been widely applied to autonomous ship navigation and maritime transportation surveillance [4]. Visual perception includes the tasks of image identification, image classification, object detection, scene understanding, and specific object recognition [5]. Machine learning techniques have become popular in the past decades for computer vision applications in transportation, with deep learning neural network approaches gaining prominence more recently [6]. Deep learning has been applied in the maritime industry for ship classification, object detection, collision avoidance, risk perception, and anomaly detection. Amongst the deep learning neural network architectures, convolutional neural network (CNN) is one type of deep learning, used for learning classification and feature extraction from training samples [5]. For instance, CNN-based YOLOv3 object recognition and image classification, are amongst the core technologies of autonomous driving technology [7].

However, machine learning vision applications require an array of sensors, cameras, radars (Lidars) as well as powerful computing and communication infrastructure onboard the autonomous vessels. In our approach, we propose instead a less networking and computationally intensive method for safety assessment in route planning. Our approach is employing a neural network to classify ship traffic images received from an infrastructure that is already available on most commercial ships today- AIS, according to their risk.

### 2.2 Data collection

Amongst the communications systems onboard ships, the Automatic Identification System (AIS) plays a prominent role as a context awareness and navigation safety device. AIS system originally designed to avoid ship collision, has more recently been used also for ship tracking [8]. AIS is a worldwide automatic positioning system based on vessel transponders that transmit a signal in the VHF band, to alert other vessels and shore stations with AIS receivers to the presence of that vessel. The signals and accompanying information can then be received by any vessel, land station or satellite, fitted with an AIS receiver, and is typically displayed on a screen of chart-plotting software application.

AIS Provides the following types of information [9]:

- Fixed, or static information including data such as: Maritime Mobile Service Identity, Call Sign and name of vessel.
- IMO Number, length and beam, type of ship and location of position-fixing antenna.
- Dynamic information, which, apart from navigational status information, is automatically updated from the ship sensors connected to AIS. This includes the ship's position with accuracy indication and integrity status, position time stamp, course over ground, speed over ground, heading, navigational status and rate of turn.

Using publicly available AIS data from Marine Traffic (www.marinetraffic.com), we recorded ship traffic in the area of interest, an area of approximately 40km2 off the English coast. The recording frequency was 10 minutes, repeated over a period of 7 days. The recorded data included the types, headings and speeds of all ships in the recorded area. Maps visualizing the ships' positions and headings were then stored as computer images. An example of such map is shown in Figure 3. Effectively, these maps visualize the relative positions and headings of the ships in the area at the time of the recording. As per the example of Figure 1, different sizes and colours of the ships indicate different types of ships (e.g. fishing boats, ferries), and speeds (e.g. fast ferries, versus slower container ships, tankers, etc.

### 2.3 Creating the test and validation image sets

We partitioned the recorded area using a grid, with the size of the grid cell selected according to rules for safe ship navigation, as explained in the following section. We manually analysed the images in all cells, and by interpreting the COLREG rules, explained in the previous section, we identified situations which represented high collision risk, as well as situations where the risk is low. The size of the selected grid cells was based on the criterion of safe distance between ships, which allow different ships to perform manoeuvres in order to cross each other's path, overtake each other and so on, without creating collision risks. As an example, the left side of the image in Figure 1 represents a high-risk situation because the ship at the bottom of the figure approaches the other ships from an inappropriate angle, and is in close proximity to them. In contrast, ships on the right side of the image are following COLREG rules, and are therefore, in a low-risk situation. Additional criteria were also employed using information about the ship type (visualized with different shape sizes and colours). As an example, the smaller ship on the left side of Figure 1, is a fishing boat which can make it harder to detect by the larger ships as it approaches them.

**Fig. 1. Examples of high (left) and low (right) risk situations**

### 2.4 Selection of Neural Net

Deep neural network have recently attracted attention because of their superior accuracy compared to previous neural network architectures. Deep neural networks can achieve human equivalent accuracy in image classification, object detection, and segmentation. In particular, Convolutional Neural Networks (CNNs) have been one of the most capable innovations in the field of computer vision, as they have outperformed traditional computer vision techniques, and have produced state-of-the-art results. CNNs have proven to be successful in many different real-life case studies and applications, such as traffic sign classification for self driving cars [10], traffic flow prediction [11] and other.

Keras [12], which was selected as the neural network framework to implement our prototype, is an open-source software library that provides a Python interface for the TensorFlow machine learning/AI library for image analysis containing pretrained image classification models. However, as such models typically were obtained from real objects and artifacts, not similar to the image patterns of our data, we had to implement and train our own neural network model.

### 2.5 CNN modeling and training

A dataset of 200 images consisting of representative examples of high and low risk pattern classes, obtained from the ship traffic grid was developed. Each image was manually labelled as high or low risk by applying safe shipping criteria. The concept of *ship domain* is often used in marine navigation and marine traffic engineering as a safety condition. The basic idea behind those applications is that an encounter of two or more ships can be considered safe if neither of ship domains is intruded by other ships [13]. For the selection of the grid cell size the safe distance between ships, approximately one nautical mile (1.852km), was used as a rule of thump. However, this safe distance can vary with ship size and type, course and speed, visibility, hydrometeorological conditions, navigational obstructions etc.

Out of the created dataset, 160 images were selected for training and 40 for validation. The images were converted to a standard 100x80 pixel, grayscale format. Due to the small size of training data, we employed data augmentation which increases the diversity of training by applying random transformations such as rotation of images.

A Convolutional Neural Network (CNN) can be viewed as a series of convolutional layers, followed by an activation function and then by a pooling (downscaling) layer, repeated many times. The pattern recognition power of CNNs comes from the repeated layering of operations, each of which can detect slightly higher-order features than its predecessor. The first layer detects simple features such as edges in an image, while subsequent layers detect hierarchically more complex images. Subsequently, as shown in Figure 2, we opted for a six layer CNN as that was deemed adequate for the complexity of the images in the dataset. Additionally, we included a dropout layer in the neural network model, which is one of the regularization techniques to reduce overfitting in deep learning models The overall architecture of the developed CNN model is shown in Figure 2.

## 3 Results analysis

After training of the network for 25 epochs and validating it, testing was carried out by using a set of test data taken from unseen images. Eight high risk images and seven low risk images were used as the test data. The classification decisions made by the neural network are shown in Table 1. From Table 1 data we calculate the True Positive Rate (TPR) of high-risk identification using Eq. 1, thus obtaining a TPR of 77.7%. Using Eq. 2 we obtain false negative rate (FNR), i.e., the ratio of high risks that have been wrongly classified as low risk by the total number of classified high risks, as 12.5%. This means that approximately 1 out of 8 high risk situations are nor detected by the system. The relative low PTR and high FNR confirm that training of the neural network using more data is required. It must be noted however that in risk management, low false negative scores are more critical than those for the other metrics.

$TPR = \frac{TP}{TP+FN}$ (Equation 1) $FNR = \frac{FN}{TN}$ (Equation 2)

$Precision = \frac{TP}{TP+FP}$ (Equation 3)

$Recall = \frac{TP}{TP+FN}$ (Equation 4)

$F1Score = (2 * \frac{Precision*Recall}{Precision+Recall})$ (Equation 5)

In a similar manner we use Eqs. 3 to 5, to obtain precision, recall and F1 scores (for high-risk class) of 0.667, 0.889 and 0.762 respectively. These scores can be improved with the addition of training data and the redesign of the neural network architecture, as explained in the final section of this paper.

### 3.1 Calculating the relative frequency of the various risk patterns

For maritime safe navigation it is useful to be able to identify the most common hazardous situations and patterns. To do so, we used a sub-image detection program [14] to analyse 82 different traffic images like the one shown in Figure 3, to find the frequency of occurrence of the different high-risk traffic patterns. We employed template matching which is a method for searching and finding the location of a template image in a larger image, available in the OpenCV computer vision library [15]. The relative frequencies of the top most frequent (unique) patterns are shown in Figure 4.

We propose that future maritime traffic monitoring systems similar to the one reported in [16], can utilise methods similar to ours, in order to analyse maritime traffic maps that are synthesized from sources of information such as AIS data, aerial data, radar data and similar sources. The traffic monitoring systems could then detect any high-risk collision situations in the current traffic, based on a library of high risk patterns such as the one proposed in this paper. As shown in Figure 3, detected images are enclosed in rectangles for easier visual identification.

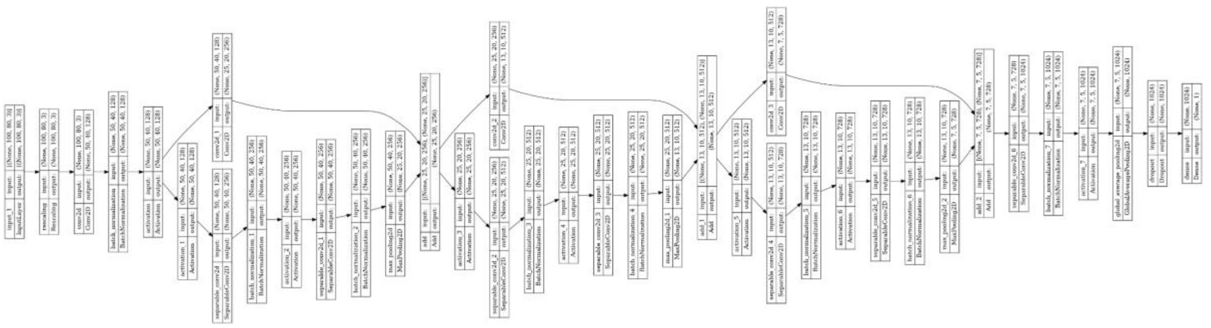
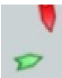
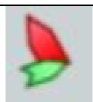
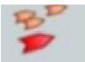
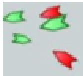
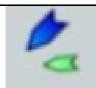
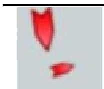
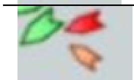
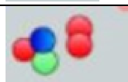
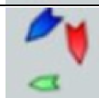


**Fig. 2. Architecture of the employed CNN**

**Table 1. CNN Classification test results**

| Pattern | (L)ow/ (H)igh risk | Classified Correctly? | High risk misclassified as low risk? | Pattern | (L)ow/ (H)igh risk | Classified Correctly? | High risk misclassified as low risk? |
|---|---|---|---|---|---|---|---|
|  | H | Y | N |  | L | Y | N |
|  | L | N | N |  | L | Y | N |
|  | H | Y | N |  | H | Y | N |
|  | L | N | B |  | H | Y | N |
|  | H | Y | N |  | L | N | N |
|  | H | N | Y |  | L | N* | N |
|  | H | Y | Y |  | H | Y | N |
| | | | |  | H | Y | N |

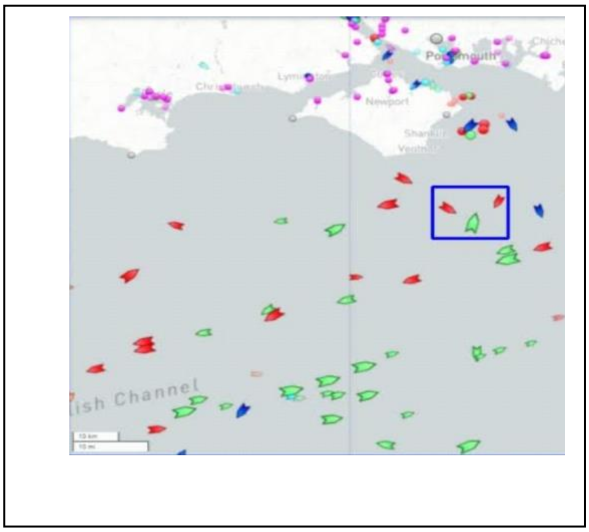


**Fig. 3. Automatic detection of high risk patterns in a traffic map**

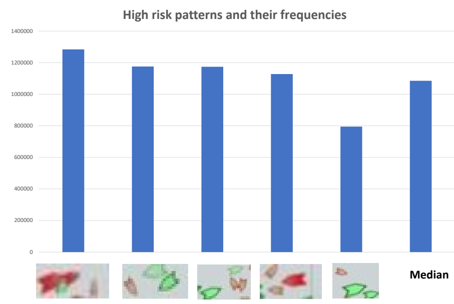



**Fig. 4. Most common unique high-risk patterns**

## 4. Discussion, conclusions and further work

The feasibility, benefits and disadvantages of the proposed approach, needs to be considered in the overall context of autonomous vehicles. and the requirements imposed by those on the data size and computational intensity of machine learning/deep learning approaches. In general, some of the main challenges when training a computer vision model involve data gathering, dataset labelling, object detection, semantic segmentation, and semantic instance segmentation. Our approach does not require the identification of discrete objects (ships), i.e., semantic segmentation, or their individuation (as 'ship1. 'ship2,..), i.e., semantic instance segmentation. Instead, our approach classifies the entire image according to its navigation risk. However, similar to all other machine learning approaches, ours also requires data gathering and labelling. Fortunately, in shipping, data gathering can rely on many diverse and usually open source datasets that are available these days from sources such as AIS. Labelling however, is currently carried out manually, something that represents a bottleneck for the efficiency of the proposed approach. Moreover, labelling must be carried out by experts in sea safety rules, i.e., it cannot easily be outsourced or crowdsourced to larger groups of (untrained) people.

Our work has contributed to autonomous route planning for unmanned sea (surface) vessels, in the broader context of autonomous robot navigation, but focusing more on route safety assessment (from a navigation perspective). Path planning is an important process for autonomous mobile robots to move from a starting point to a destination without hitting any obstacles [17]. Path planning can in general, by divided into global path planning when robots have information about the environment such as obstacles, and local path planning where such information is not available, possibly because the environment is dynamic [17]. In this sense, our approach can be applied to both global and local path planning, in the sense that the autonomous ship planner can first plan a safe route based on the traffic pattern image classification of the traffic pattern images, but as the plan is executed the potentially changed environment needs to be re-assessed periodically, since new ships or other obstacles can appear, or ships may change their position and course unexpectedly.

There are several paths for extending the research described in this paper, that include:

- Expansion of the classification range of traffic pattern from binary (i.e., 'risk' or 'no risk') to multi-valued where different degrees of risk (e.g., 'low', 'medium', 'high') can be defined, expressed as crisp or fuzzy values. A multi-level classification of risk would enable more sophisticated route planning algorithms to be developed for the autonomous route planner.
- Experimentation with different, more efficient, image classification neural networks such as Vision Transformers (ViT). Recent research has demonstrated that ViTs exhibit better performance and greater efficiency than CNNs [18].
- Combination of our approach with other route planning algorithms such as velocity obstacle (VO), which is a technique that calculates the set of all velocities of a robot that will result in a collision with another robot at some moment in time, assuming that the other robot maintains its current velocity.[19] In the context of autonomous route planning, the route planner would use the planned vessel speed to calculate the VO and then use the traffic map to select the relevant image, based on chosen direction and speed. Next, based on the collision risk of the image, the route planner might decide to alter speed or course in order to avoid the collision risk.
- Continuous training: In the current approach models are trained before deployed. However, autonomous ship navigation requires reasoning and decision-making based on environmental information in real time [4]. One of our future research plans is to solve this problem.
- Expansion of the neural network training set, with additional images obtained from AIS datasets and other sources: In general, it is relatively easy to obtain additional ship traffic data from sources such as those reported above, however there is a bottleneck in the process of manually classifying (labelling) such data before they can be used for training the neural network. Towards alleviating this obstacle, automatic or semiautomatic labelling techniques could be investigated. As said previously, it is, however, important that any future image classification systems primarily minimize the false negative detection rate, as failing to detect potentially dangerous situations represents a serious shortcoming.

In conclusion, this paper has proposed a novel approach for the detection of collision risk situations in maritime traffic, that relies on the analysis of ship traffic imagery with the use of deep learning image classification techniques. Collision risk is a threat for the shipping industry and the rules for safe navigation are both complex and, in some aspects, ambiguous. This, combined with advances in autonomous ships makes more important the development of robust techniques for situation awareness and collision avoidance in shipping and maritime.

## References


[1] Öztürk Ü, Akdağ M, Ayabakan T. A review of path planning algorithms in maritime autonomous surface ships: Navigation safety perspective. Ocean Engineering. Volume 251, 1 May 2022.

[2] Sviličić Š and S Rudan. Modelling Manoeuvrability in the Context of Ship Collision Analysis Using Non-Linear FEM. J. Mar. Sci. Eng. 2023, 11(3), 497; https://doi.org/10.3390/jmse11030497 - 25 Feb 2023

[3] Campbell S, Naeem W, Irwin GW. A review on improving the autonomy of unmanned surface vehicles through intelligent collision avoidance manoeuvres. Annual Reviews in Control 36 (2012) 267–283.

[4] Zhang Ruolan , Shaoxi Li, Guanfeng Ji, Xiuping Zhao, Jing Li, Mingyang Pan, "Survey on Deep Learning-Based Marine Object Detection", Journal of Advanced Transportation, vol. 2021, https://doi.org/10.1155/2021/5808206

[5] Hironobu Fujiyoshi, Tsubasa Hirakawa, Takayoshi Yamashita. Deep learning-based image recognition for autonomous driving IATSS Research Volume 43, Issue 4, December 2019, Pages 244-252

[6] Sviličić Š and S Rudan. Modelling Manoeuvrability in the Context of Ship Collision Analysis Using Non-Linear FEM. J. Mar. Sci. Eng. 2023, 11(3), 497; https://doi.org/10.3390/jmse11030497 - 25 Feb 2023

[7] Yeo Hyeongi Autonomous Driving Technology through Image Classification and Object Recognition based on CNN ICVISP 2020: Proceedings of the 2020 4th International Conference on Vision, Image and Signal Processing December

[8] Yan Zhaojin, Yijia Xiao, Liang Cheng, Rong He, Xiaoguang Ruan, Xiao Zhou, Manchun Li, Ran Bin. Exploring AIS data for intelligent maritime routes extraction. Applied Ocean Research. Volume 101, August 2020, 10227.

[9] Brunelli R, Template Matching Techniques in Computer Vision: Theory and Practice, Wiley, ISBN 978-0-470-51706-2, 2009

[10] Olindersson F and Janson CE. Development of a software to identify and analyse marine traffic situations. MARSIM 2015, Newcastle, UK. September 2015.

[11] Zhang HY ,Lin WM, Chen AX. Path Planning for the Mobile Robot: A Review. Symmetry 2018, 10(10), 450.

[12] Keras https://keras.io/examples/vision/ [Accessed: 2023-03-20]

[13] Szlapczynski Rafal, Przemyslaw Krata, Joanna Szlapczynska. Ship domain applied to determining distances for collision avoidance manoeuvres in give-way situations. Ocean Engineering Volume 165, 1 October 2018, Pages 43-54

[14] Oneil, J. Subimage/ https://github.com/johnoneil/subimage [Accessed: 2023-03-15]

[15] MarineInsight. The definitive AIS Handbook. Available from https://www.marineinsight.com/wp-content/uploads/2016/11/AiS-Whitepaper.pdf. [Accessed: 2023-02-15]

[16] Palak and A. L. Sangal, "Traffic Signs Classification using Convolutional Neural Networks: A review," 2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC), Jalandhar, India, 2021, pp. 450-455, doi: 10.1109/ICSCCC51823.2021.9478172.

[17] Wang T, Zhang, B, Wei W, Damaševičius R, Scherer R. Traffic flow prediction based on BP neural network, 2021 IEEE International Conference on Artificial Intelligence and Industrial Design (AIID), Guangzhou, China, 2021, pp. 15-19, doi: 10.1109/AIID51893.2021.9456479.

[18] Bai Y, Mei J, Yuille A, Xie C. Are Transformers More Robust Than CNNs? arXiv:2111.05464

[19] Fiorini P, Shiller Z. Motion planning in dynamic environments using velocity obstacles. The International Journal of Robotics Research. 17 (7): 760–772. July 2018